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A fuzzy c-means based hybrid evolutionary approach to the clustering of supply chain ☆

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A B S T R A C T

This paper describes the work that adapts group technology and integrates it with fuzzy c-means, genetic algorithms and the tabu search to realize a fuzzy c-means based hybrid evolutionary approach to the clustering of supply chains. The proposed hybrid approach is able to organise supply chain units, transportation modes and work orders into different unit-transportation-work order families. It can determine the optimal clustering parameter, namely the number of clusters, c, and weighting exponent, m, dynamically, and is able to eliminate the necessity of pre-defining suitable values for these clustering parameters. A new fuzzy c-means validity index that takes into account inter-cluster transportation and group efficiency is formulated. It is employed to determine the promise level that estimates how good a set of clustering parameters is. The capability of the proposed hybrid approach is illustrated using three experiments and the comparative studies. The results show that the proposed hybrid approach is able to suggest suitable clustering parameters and near optimal supply chain clusters can be obtained readily.

1. Introduction

Supply chain management is about coordinating and managing an entire value chain, from customer order to production, storage, distribution and delivery. A supply chain, one that supports global manufacturing in particular, may be enormous in terms of size and number of supply chain units (Goh & Gan, 2005). In reality, a supply chain may have multiple end products with shared components, facilities, capacities and suppliers. The flow of materials is therefore not always along an arborescent network. This further increases the complexity of supply chain management. Thus, to deal with a sizeable supply chain that may grow beyond the ability of existing optimisation approaches to cope, a more robust methodology is necessary. It is envisaged that clustering technique, which is able to decompose a complex problem into smaller and controllable ones, would help in reducing the search space and improving the efficiency of search procedures in order to derive better solutions for an entire supply chain. In this respect, group technology (GT), which was first suggested by Burbridge (1975), can possibly be adapted and used to cluster a supply chain.

Basically, GT is a technique that can be used to identify and group together similar parts and manufacturing operations or processes into part families (Khoo et al., 2003; Snead, 1989). For example, a family of parts is made up of components that can be manufactured by similar machinery, tooling, machine operations and jigs and fixtures. Once the part families have been formed, machines are often organised into manufacturing cells and the families of parts are assigned to cells according to their routing. It is postulated that the basic notions of GT can be borrowed and enhanced using such techniques as fuzzy clustering theory and graph theory to realize a comprehensive model or representation for the handling of supply chain management problems. In doing so, a complex supply chain can possibly be decomposed into "well coordinated" supply chain clusters comprising supply chain units, transportation modes and work orders.

There are four basic methods that can be used to form part families (Bedworth, Henderson, & Wolfe, 1991; Chu & Hayya, 1991; Offodile, Mehrez, & Grznar, 1994). They are: (i) visual method, (ii) parts coding analysis, (iii) by analysing component or production flow and (iv) by applying optimisation algorithms. This work focuses on optimisation algorithms as the first three approaches are difficult to be adapted to cluster supply chains. Some common algorithms employed to create manufacturing cells include Bond Energy (Currie, 1992; Suresh & Kaparthi, 1994), Rank Order Clustering (King, 1980), and Direct Clustering (Miltenburg & Montazemi, 1993; Mukhopadhyay, Sarkar, & Panda, 1994). All of them represent machines (in rows) and parts (in columns) as a matrix. More advanced techniques include Simulated Annealing (Chen & Srivastava, 1994; Pailla, Trindade, Parada, & Ochi, 2010; Souilah, 1995; Zolfaghari & Liang, 1998), Neural Networks

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(Chattopadhyay, Sengupta, Ghosh, Dan, & Mazumdar, 2013; Lozano, Guerrero, Eguia, Canca, & Smith, 1998; Wang & Yoshiyasu, 1993) and Genetic Algorithms (Gupta, Gupta, Kumar, & Sundaram, 1996; Khoo et al., 2003; Paydar & Saidi-Mehrabad, 2013; Rao, Pham, & Gu, 1999; Venugopal & Narendran, 1992; Yin & Khoo, 2011).

One assumption made when applying traditional optimisation algorithms is that part and machine families are mutually exclusive. Accordingly, each part can only belong to one part family and each machine to one machine family. However, in reality, the relationship between parts and machines can be less obvious, and human intervention and further analysis may have to be performed. Thus, fuzzy clustering appears to be a more appropriate technique to deal with machine cell formation problem in a complex real manufacturing environment.

Fuzzy models are good for expressing the fuzziness in a system. As already mentioned, traditional approaches used in GT (Snead, 1989) such as mathematical programming, cluster analysis and heuristics assume that a given part or a machine can be a member of only one part-family or a machine-cell respectively. Also, whenever new parts or machines have been introduced into the production system, the entire GT problem needs to be re-assessed.

The foundation of fuzzy clustering is fuzzy set theory (Lowen, 1996). Fuzzy set theory as its name suggests, is basically a theory of classes with blurred boundaries. In a conventional set concept (crisp set), an element is either a member of a set of not. Fuzzy sets on the other hand, allow an element to be partially in a set. Each element is given a degree of membership. This membership value can range from '0' (not a member of the set) to '1' (a member of the set). A membership function expresses the relationship between the value of an element and its degree of membership in a fuzzy set. Fuzzy sets are able to handle preciseness that may exist in the parameters of a system.

Recently, more and more researchers use genetic algorithm (GA) based fuzzy c-means (FCM) to solve different problems. Image segmentation problem (Awad, Chehdi, & Nasri, 2009; Benaichouche, Oulhadj, & Siarrym, 2013; Cheng & Gong, 2008), model detection of a distributed sensor networks (Korjani, Afshar, Menhaj, & Rajati, 2007) and data mining (Aydilek & Arslan, 2013; Huang, 2012; Yan & Li, 2008) are some of them. There are also studies on the application of evolutionary algorithm based fuzzy c-means to GT (Li, Gao, & Ji, 2002; Papaioannou & Wilson, 2010; Yin & Khoo, 2011; Zhao, Tsujimura, & Gen, 1996). These applications require the values of clustering parameters such as number of clusters (c) and weighting exponent (m) to be predefined or predetermined by additional steps. In this work, a novel fuzzy c-means based hybrid evolutionary approach to the clustering of supply chain is proposed. The proposed approach is able to determine the optimal clustering parameters, c and m, of fuzzy c-means (FCM) automatically.

The rest of the paper is organised as follows. Section 2 describes an overall framework of a prototype distributed intelligent coordination and scheduling system that embodies the proposed fuzzy c-means based hybrid evolutionary approach. The details of the proposed approach are presented in Section 3. The effectiveness of the proposed approach is illustrated using three experiments and the comparative studies and the results obtained are reported in Section 4. The last section, Section 5, summarises the main conclusions reached in this work.

2. An overview of a prototype distributed intelligent coordination and scheduling system

Yin and Khoo (2007b) developed a prototype distributed intelligent coordination and scheduling system (Fig. 1) that is able to support a seamless materials flow network within a global manufacturing environment. As shown in Fig. 1, the prototype system comprises three main modules, namely Routing and Sequence Optimiser (RSO), Supply Chain Virtual Clustering (SCVC) and Supply Chain Order Scheduler (SCOS). Basically, the RSO (Yin & Khoo, 2007a) module is used to provide the SCVC module with a reasonably good routing and order processing combination by considering the capacity of each supply chain unit and the business strategy to maintain the required customer service level and competitiveness. Typical formulae for the evaluation of costs and customer service level can be found in Yin and Khoo (2007a).

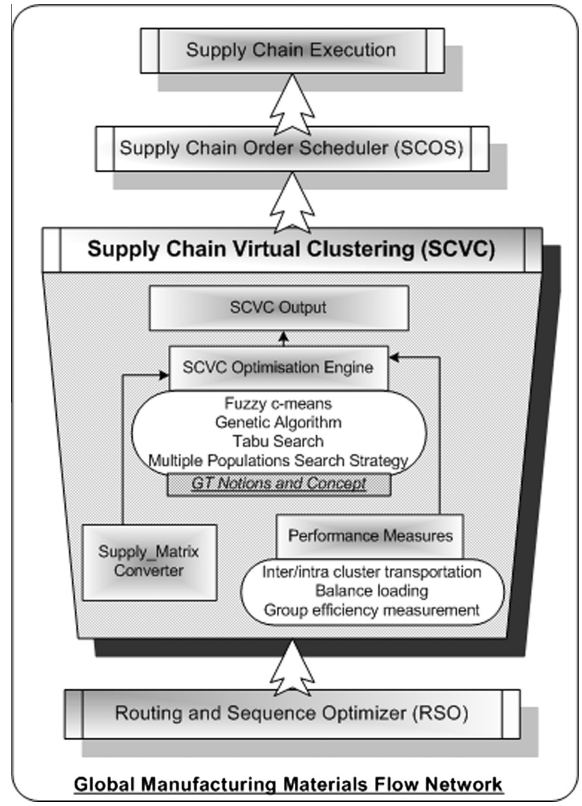

Fig. 1. A framework of a prototype distributed intelligent coordination and scheduling system.

The SCVC module then attempts to compartmentalize a large supply chain optimisation problem that can hardly be solved by traditional algorithms into manageable sub-problems. Subsequently, the SCOS module, which comes with an agent-based distributed coordination and scheduling mechanism, attempts to provide an optimised schedule for the supply chain.

As mentioned, supply chain optimisation problems are complex and can hardly be solved by traditional algorithms due to combinatory explosion. This work focuses on the realization of the SCVC module. Basically, the SCVC module is employed to organise the supply chain units, transportation modes and work orders into different unit-transportation-work order families (Khoo & Yin, 2003). As a result, the search space of a complex supply chain problem can be reduced considerably.

Fig. 1 shows the key functional sub-modules of the SCVC module. They are:

(1) Supply_Matrix Converter. It retrieves a Supply_Graph (Khoo & Yin, 2003) and the relevant Supply_Graph matrix of each work order and converts it into a Supply_Matrix (Section 3.1) that is used for virtual clustering.
(2) Performance Measure. It calculates a so-called validity index for fuzzy c-means. The validity index serves as an objective