A hierarchical model for extended supply chain coordination and optimization

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**A HIERARCHICAL MODEL FOR
EXTENDED SUPPLY CHAIN COORDINATION
AND OPTIMIZATION**

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2011

A HIERARCHICAL MODEL FOR EXTENDED SUPPLY CHAIN COORDINATION AND OPTIMIZATION

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ABSTRACT

Supply chain management is about coordinating and managing the entire value chain, from customer order to production, storage, distribution and delivery. However, different function units along a supply chain have their own purpose and operate independently. This research presents an in-depth study aiming at realizing a hierarchical model and a framework for supply chain coordination and optimization. It is envisaged that the proposed model can be used as a tool to facilitate planning, optimize the detailed schedules of the various supply chain units such as manufacturing plants, suppliers and distribution centres and support global manufacturing.

Accordingly, a prototype distributed intelligent system for multi-level supply chain coordination, optimization and order scheduling (SCASO) has been established. The prototype SCASO system comprises three main modules, namely Routing and Sequence Optimizer (RSO), Supply Chain Virtual Clustering (SCVC) and Supply Chain Order Scheduler (SCOS). Basically, the RSO module is used to provide the SCVC with a reasonably good routing and order processing sequence combination while taking into account the capacity of each supply chain unit and the business strategy to maintain the required customer service level and competitiveness. The SCVC module then attempts to compartmentalize an extended supply chain optimization problem that can hardly be solved by conventional algorithms into manageable sub-problems. Subsequently, the SCOS module, which contains an agent-based distributed coordination and scheduling mechanism, integrates scheduling with supply chain optimization.

The key methodologies and algorithms that enable the prototype SCASO system have also been formulated and implemented. These include: i) a multiple populations search strategy based evolutionary approach (MBEA), which is a generic methodology for solving different optimization problems in this work; ii) a novel graph representation known as Supply_Graph, which is employed to represent and analyze the complex business processes and order routings; iii) a so-called Supply_Matrix to channel information from Supply_Graph to the SCVC module for further processing; iv) an exact schema theorem for genetic algorithms

(GAs). The exact schema theorem is used to examine the optimal/compromised crossover and mutation probabilities that may improve the performance of GAs; and v) an enhanced fuzzy c-means technique for the clustering of supply chain units. The capability of the prototype SCASO system has been illustrated using a case study gleaned from a semiconductor packaging industry.

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List of Abbreviations

AHP	Analytical Hierarchy Process
BOM	Bill of Materials
CIMOSA	Computer Integrated Manufacturing Open System Architecture
DA	Die Attach (a semiconductor packaging process)
DC	Distribution Centre
EOL	End of Line (semiconductor packaging processes)
ERP	Enterprise Resource Planning
FCM	Fuzzy C-Means
FG	Finished Goods
FOL	Front of Line (semiconductor packaging processes)
GA	Genetic Algorithm
GT	Group Technology
IC	Integrated Circuit
ICT	Information and Communication Technologies
IT	Information Technology
JIT	Just-in-Time
KBS	Knowledge-Based System
MBEA	MPSS Based Evolutionary Approach
MIP	Mixed Integer Programming
MPSS	Multiple Populations Search Strategy
MRP	Material Requirement Planning
MRP II	Manufacturing Resource Planning
PCBA	Printed Circuit Board Assembly
PGP	Pre-emptive Goal Programming
PSA	Problem Specific Algorithms
RSO	Supply Chain Routing and Sequence Optimizer
SCASO	Supply Chain Coordination and Schedule Optimization System
SCCA	Supply Chain Cluster Agent
SCM	Supply Chain Management
SCOR	Supply-Chain Operations Reference
SCOS	Supply Chain Order Scheduler
SCSA	Supply Chain Supervisory Agent
SCSC	Supply Chain Scheduling Client
SCSM	Supply Chain Scheduling Master

SCVC	Supply Chain Virtual Clustering
TOC	Theory of Constraints
TQM	Total Quality Management
TS	Tabu Search
WB	Wire Bond (a semiconductor packaging process)
WLCSP	Wafer Level CSP

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Chapter 1 INTRODUCTION

1.1 Background

Supply chains are used extensively in almost every industry and organization, although their complexity may vary greatly from industry to industry and from organization to organization. For example, in Ford, which was a complex vertical integrated organization when it was first started, its corporate's objective was ownership-based control (Bowersox and Closs 1996). In order to build a self-sufficient industrial empire, they invested in coal mines, timberlands, glass factories, and even land to grow soybeans for manufacturing paint. They also developed a huge manufacturing complex that comprised an inland port and an intricate network of rail and road transportation to ensure a reliable supply of materials by controlling far beyond its core businesses. However, in their final analysis, Ford found that no organization could be self-sufficient due to the very high costs, low return on investment and lack of expertise. As a result, their investment and resources were subsequently shifted to develop, improve and maintain their core manufacturing and other competencies, and the functions and activities outside their core competencies were covered by developing channel relationship with other specialized organizations, which might provide cost effective and better quality services than their own bureaucracy.

In recent years, the above-mentioned channel relationship has been further enhanced. As a consequence, a supply chain that integrates critical processes and functions becomes necessary in order for companies to compete in the global arena (Gourdin 2006). Business partners can also realize a virtual enterprise which is a temporary alliance of enterprises that share capabilities/skills/core competencies and resources in order to realize a better business

opportunity. Suppliers, manufacturers and customers can form business partnerships, which are operative/short-term, tactical/medium-term or strategic/long-term depending on specific requirements among the business partners. In general, a supply chain encompasses all the activities associated with the flow and transformation of goods from the raw materials stage, through to the end user, as well as the associated information flows. Materials and information flow both up and down the supply chain (Ross 2003, Schniederjans *et al.* 2010). Products must flow smoothly from suppliers to manufacturer, through distribution, and need to be delivered with a high level of service to final customers. Furthermore, in order to achieve shorter time to market and reduce inventory costs, enterprises must focus on designing an extended supply chain (Martin and Patterson 2009, McCormack and Kasper 2000, Wailgum 2008) which includes supply networks, distribution networks, and alliance networks. Thus, an extended supply chain provides an avenue to include every company that contributes to the development of a product. It extends the scope of a supply chain from centre business or operation to include other entities or partners such as direct suppliers or suppliers' suppliers that provide resources and services, and clients, distributors and all intermediaries between business operators and end users. Due to globalization, it is important for a company to keep track of the happenings in its extended supply chain as they might have an impact on the company itself. For example, a strike in a copper alloy supplier might cause a lead frame manufacturer to run out of raw materials. This could eventually affect the operation of a semiconductor packaging company as lead frame is a key direct material used in die-attach operation. If the semiconductor packaging company knows what is happening in its extended supply chain through data sharing and information technology (IT) it could probably find another lead frame supplier that can ensure a smooth supply of the lead frame.

Supply chain management provides a tool through which such a channel relationship can be achieved. It is about coordinating the various components of the entire value chain, from customer order through production, storage, distribution and delivery. In order to optimize

the performance, supply chain functions must operate in a coordinated manner. For example, Chrysler Corporation (CC), as a major international automobile manufacturer, began pushing for developing cross-functional integration since early 1990's which extended to its supply base as almost 80% of its revenue was spent on purchasing components from its suppliers (Newman *et al.* 2009). Customer-supplier relationship in its supply chain has been studied in different domains such as sharing schedule using electronic data interfaces (EDI), vendor managed inventory and supplier portal to promote the coordination. However, the dynamic of enterprise and market makes the coordination and information sharing difficult. A comprehensive and effective model to facilitate the coordination along the entire supply chain is therefore necessary for the purpose of optimization. Many researchers (Lakhal *et al.* 2001, Luo *et al.* 2001, Zhong *et al.* 2008) have attempted to bridge the gap among the various functions of an enterprise. Software agents (Chen *et al.* 2009, Dumond and Roche 2000, Xue *et al.* 2005), mathematical modelling such as mixed integer programming and linear programming (Elmaraghy and Majety 2008, Leung *et al.* 2002, Zapfel and Wasner 2002), Petri nets (Raghavan and Viswanadham 1999), blackboard based system (Ito and Salleh 2000), artificial intelligence (Chen *et al.* 2009, Feng and Wang 2008), and simulation (Archibald *et al.* 1999, Padmos *et al.* 1999) were employed to develop various supply chain systems.

It is apparent that production facilities are often more complex than other units of a supply chain, such as warehouses and retailers, in terms of resources constraints, and dynamic of production. Researchers also examined the possibility of integrating manufacturing scheduling with supply chains as the variation in factory schedule might adversely affect the overall performance of a supply chain (Lendermann *et al.* 2001, Kreipl and Dickersbach 2008, Nurmilaakso 2004, Sawik 2009).

1.2 Objective of the Research

The objective of this research is to carry out an in-depth study on how to realize a hierarchical model and a framework of a distributed intelligent system for multi-level supply chain coordination, optimization and order scheduling. It is envisaged that the hierarchical model established in this work is able to handle extended supply chain optimization problems and would help the planning and scheduling of supply chain units, such as suppliers, manufacturing plants, warehouses, distribution centres and customers. It would also support an extended supply chain and a global manufacturing environment, which takes into account suppliers' and customers' supply chain networks.

1.3 Research Scope

In order to realize the proposed hierarchical model and a framework for extended supply chain coordination and schedule optimization, critical issues concerning an holistic representation of a supply chain, advanced computational algorithms and intelligent decision support systems to facilitate the coordination and planning of a supply chain, and the detailed scheduling optimization of supply chain units need to be addressed.

This research covers the followings:

- (1) A hierarchical model and a framework for supply chain coordination and optimization.
- The development of a framework that supports the hierarchical coordination and optimization of the entire supply chain.
- An investigation into work order routing selection and sequence optimization. This would involve the realization of a more robust optimization technique based on search algorithms such as genetic algorithms (GAs) and the tabu search (TS).
- The establishment of a virtual clustering methodology. The basic notions of group technology (GT) are adapted and enhanced using such technique as fuzzy c-means. In

so doing, it is anticipated that the search space for the optimization of a complex supply chain can be reduced.

- An investigation into an intelligent agent based mechanism for information exchange and coordination. When coupled with a scheduling engine, the mechanism can possibly facilitate and promote the negotiation and coordination among supply chain units so as to obtain a near global optimal schedule for a supply chain.

(2) Key methodologies and algorithms.

- Supply chain modelling and representation using the Supply Chain Operations Reference (SCOR) Model. For the purpose of illustration, a typical supply chain will be designed and modelled using the Supply-Chain Operations Reference (SCOR) model.
- Graph representation. A novel graph representation to depict an extended supply chain will be established. Such a representation enables a supply chain to be modelled and the logical relationship among the nodes on the graph to be expressed.
- GA and exact schema theorem. An exact schema theorem for genetic algorithms (GAs) will be formulated. The proposed exact schema theorem extends Goldberg's schema theorem. It can be employed to predict the expected number of copies of schemas in the next GA generation. Leveraging on the exact schema theorem, the existence of the optimal or a compromised pair of crossover and mutation probabilities will be examined.
- Multiple populations search strategy based evolutionary approach (MBEA). The proposed MBEA comprises five different layers and are used to fulfil different functionalities. It provides a generic methodology and can be applied to solve different optimization problems.
- Group technology and fuzzy c-means. The notions of group technology are borrowed and extended to realize a supply chain virtual clustering. Fuzzy c-means is then incorporated into MBEA to realize a hybrid technique to search for the near optimal fuzzy cluster matrix as well as the number of cluster centres and the weighting exponent.

- (3) A prototype system and a case study. Realization of a prototype system to illustrate the proposed framework, the ability of the novel approaches and the methodologies as well as algorithms developed in this work. The effectiveness of the prototype system will then be demonstrated by a case study.

1.4 Organization of the Thesis

The organization of this thesis is as follows.

Chapter 2 provides a comprehensive review on supply chain management, and supply chain function units optimization. Some research areas, which have been well addressed in the literature, are discussed. In addition, the importance of integrating detailed scheduling with supply chain optimization is explained. A detailed discussion on the key methodologies and algorithms that are related to this work is presented. They are group technology (GT), fuzzy c-means, genetic algorithm (GA), the tabu search (TS) and the Schema Theorem. It includes also a brief review on the Supply-Chain Operations Reference (SCOR) model proposed by the Supply-Chain Council.

Chapter 3 describes a distributed hierarchical model and a framework for extended supply chain coordination and optimization. The supply chain coordination and schedule optimization system (SCASO) comprises three main modules, namely Routing and Sequence Optimizer (RSO), Supply Chain Virtual Clustering (SCVC) and Supply Chain Order Scheduler (SCOS). The modelling of a typical supply chain using SCOR is depicted. Manufacturing plants, warehouses, distribution centres, transportations, suppliers and customers are designed and discussed to tackle the short-term operational supply chain optimization. Chapter 3 also includes a discussion on a novel multiple populations search strategy based evolutionary approach (MBEA) that is embedded into the RSO and SCVC to handle supply chain optimization problems.

Chapter 4 proposes a graph representation, which is coined Supply_Graph, to model and

analyze the business processes of the supply chain from customer orders to suppliers. Logical relationships are superimposed onto the Supply_Graph to enable the modelling of a complex supply chain with multiple level assemblies, transportations, multiple split and merging of orders and cross-boundary virtual enterprises. Furthermore, an exact schema theorem that attempts to explore the possibility of deriving optimal crossover and mutation probabilities, i.e. p_c and p_m respectively, for genetic algorithms are studied. A MBEA enabled fuzzy c-means approach, which can simultaneously search for a compromised pair of p_c and p_m , is then proposed and sample data sets are used to examine the existence of the compromised GA parameters.

Chapters 5, 6 and 7 outline the detailed designs and implementations of the three modules of the SCASO, namely RSO, SCVC and SCOS, respectively. The MBEA enabled optimization algorithms and hybrid heuristics of the RSO and SCVC modules are proposed. An intelligent agent-based system is also established in order to realize the SCOS module in Chapter 7.

A comprehensive case study based on a leading assembly and test service provider for the semiconductor packaging industry in Singapore is reported in Chapter 8. It is used to illustrate the effectiveness and capability of the proposed prototype SCASO system. Chapter 9 summarizes the main conclusions reached in this work. It also outlines some suggestions for future work that can enhance the present prototype SCASO system.

Chapter 2 LITERATURE REVIEW

2.1 Supply Chain Management

Supply chain management concerns the implementation of a “supply chain orientation” across suppliers and customers (Mentzer 2001). It involves systematic and strategic coordination of traditional business functions within a particular company and across businesses in a supply chain. It aimed at improving the long-term performance of the individual companies and the supply chain as a whole. In other words, a supply chain comprises a worldwide network of facilities and distribution options that performs the functions of procurement of materials, transformation of these materials into intermediate and finished products, and the distribution of these finished products to customers. Traditionally, marketing, distribution, planning, manufacturing, and purchasing organizations in a supply chain operate independently. These organizations have their own goals, which are often conflicting. For example, the marketing strategy to achieve high customer service and maximum sales dollars may contradict manufacturing and distribution goals (Fawcett *et al.* 2008, Infosciler 2003). Frequently, many manufacturing operations are designed to maximize the throughput and minimize costs with little consideration for the impact on inventory levels and distribution capabilities, and purchasing contracts are often negotiated with very little information beyond historical purchasing patterns (Infosciler 2003). It is apparent that there is no single, integrated plan for an organization. Thus, supply chain management is a strategy through which such an integration can be achieved.

As shown in Figure 2-1, the supply chain units are geographically distributed all over the world. A manufacturer in China may have a material supplier in United States of America

and sales and retailers in Europe (Lenovo 2010). Figure 2-2 shows a supply chain which includes suppliers, manufacturing plants, warehouses, retailers and consumers. Raw materials are delivered from suppliers, transformed into commercial goods by manufacturing plants, and then transported to distribution centres (DCs) and/or warehouses, and ultimately, to end users or consumers through retailers (Figure 2-2).

Figure 2 - 1 Geographic product flow in a supply chain

Figure 2 - 2 An example of a supply chain (Adapted from Yin and Khoo 2007b)

As shown in Figure 2-3, the materials and information flows connect different functional units of the supply chain, which coordinates the whole value chain, from the procurement of

materials from suppliers to manufacturing, storage, distribution and delivery of final product to customers.

- **Materials flow:** From the initial purchase of materials or a component, the supply chain functional units add value at each step of its transformation from materials into finished products.

Figure 2 - 3 Flow of functional units of a supply chain

- **Information flow:** Information normally comprises two major types of flows: coordination and operational flows. Coordination is the backbone of the overall supply chain. Forecast, strategic objectives, procurement, physical distribution and manufacturing requirements must be integrated to facilitate the overall integrated performance. The operational flow is to provide the detailed data for integrated performance of physical distribution, manufacturing support and procurement by dealing with the order management, inventory management, transportation, distribution and so on.
- **Monetary flow:** business needs a healthy cash flow cycle for its growth. The flow of money along the supply chain is as critical as the flow of goods and information. However, as monetary flow is not the focus of this work, it will not be covered in the following chapters.
- **Physical distribution:** Physical distribution concerns the movement of finished products which links manufacturing plants, distribution centres, warehouses and retailers to provide products to the customers.
- **Procurement:** Procurement deals with the purchase and arrangement of materials,

components and half finished product to manufacturing or assembly plants and warehouses.

- **Manufacturing:** Manufacturing transforms materials and components into finished products.

2.1.1 Evolution of Supply Chain Management

The evolution of supply chain management has been discussed by Ross (2003) and Li (2007). Basically, supply chain management can be categorized into five distinct management stages from the late 19th century to the early 21st century (Table 2-1). They are: (i) stage of logistics decentralization and inventory management; (ii) stage of total cost management and material requirement planning (MRP); (iii) stage of integrated functions and manufacturing resource planning (MRP II); (iv) stage of enterprise resource planning (ERP) and supply chain management (SCM); and (v) stage of e-supply chain management.

- (1) **Stage 1 - logistics decentralization and inventory management.** The logistics during this stage was viewed as an intermediary function concerned with inventory management and delivery. Logistics activities were divided among operation functions, such as sales and production. It resulted in a disjointed and uncoordinated logistics management. Since there were no global competitions and mass production and mass distribution were still the focus of business strategy, logistics decentralization was a minor problem for most companies even it incurred costly management. Company's management focuses were mainly on the individual operation performance and inventory/transportation management.
- (2) **Stage 2 - total cost management and MRP.** Due to the development of new concepts of marketing, pricing and promotion, and the explosions in production lines, reducing the total cost in order to compete in the market became a key element. Logistics functions had been merged and centralized in a single department in order to reduce the costs associated with inventory and distribution. Management concepts such as just-in-time (JIT), zero inventories and quality management had been proposed to maintain the

customer service level while reducing the total cost. MRP software and applications were first introduced by IBM as computers became more sophisticated and less costly. MRP was able to identify what product was required by customers and check against the on-hand inventory level. Shortage could also be calculated and plan was worked out for production. As MRP by itself didn't take into consideration the capacity limitation, a closed loop MRP was soon been introduced to consider the capacity requirement when the computational power of a computer was improved.

- (3) Stage 3 - integrated functions and MRP II. MRP and closed loop MRP had evolved in this stage into MRP II. Closed loop capacity planning and financial management functions were incorporated into MRP II to ensure effective planning, control and management of all the resources of a manufacturing company. Management concepts and philosophies such as JIT, theory of constraints (TOC) and total quality management (TQM) equipped the companies with tools to minimize cost and process lead-time and maximize production flexibility and responsiveness to dynamic environment. In order to maintain the competitive advantage, companies started to understand that competitive values such as material availability and speed of delivery could be achieved by creating the channel relationship and working together with other supply chain trading partners.
- (4) Stage 4 – ERP and SCM. Channel relationship and channel management functions at this stage had been developed into supply chain management mainly due to the acceleration of globalization, organizational reengineering, and the development of information technologies. Through SCM applications that connected the entire supply channels, enterprise could leverage channel competencies and viewed channel partners as part of the “virtual organization” which could share capabilities/skills/core competencies and resources in order to realize a better business opportunity. The development of ERP system integrated the stand-alone isolated systems and created the complete visibility of information across functions within an organization.
- (5) Stage 5 – e-supply chain management. At this stage, the e-business had been integrated into a supply chain network to synchronize the channel functions of the entire supply chain into a single, flexible and scalable “virtual” enterprise. It was capable of

optimizing core competencies and resources leveraging the Internet and other information systems and information and communication technologies (ICT). Business intelligence that included decision support systems, statistical analysis, forecast and data mining had been introduced to help the organization development. This stage is further explained in Section 2.1.2.

Table 2 - 1 Evolution of supply chain management (adapted from Ross 2003 and Li 2007)

No	SCM Stage	Management Focuses	Organizational Consequences
1	Until early 60s Logistics decentralization Inventory management	Operations performance Warehousing and inventory management Transportation efficiencies Specializing and focusing on local markets	Decentralized logistics functions Small firms Simple management structure Slow transportation
2	Mid 60s to 70s Total cost management and MRP	Logistics centralization Total cost management Operations optimization Customer service	Centralized logistics functions Application of computers New management concepts (JIT, zero inventory)
3	1980s Integrated functions and MRP II	Logistics planning Integration with enterprise systems and functions Integration with channel operations functions Total quality management	Supply chain planning Integrated enterprise systems New management concepts (TQM, TOC)
4	Late 80s to 90s ERP and SCM	Growth of co-evolutionary channel alliances Collaboration to leverage channel competencies Information technology and the Internet Organization visibility and system integration through ERP Resource optimization	Supply chain network / trading partner network Virtual organizations Globalization
5	Year 2000 and beyond e-Supply chain management	Application of the Internet and IT/ICT to the SCM concept e-business/e-commerce integration Business intelligence	Multiple enterprise supply chain Complex management structure

The evolution of the SCM is highly related to the development of the ERP. In their earlier stage, MRP/MRP II is one of the core functions of both systems while SCM emphasises more on the logistics integration and ERP on the manufacturing integration. Many SCM applications rely on the ERP to provide the up-to-date information as ERP integrates all the

information together in a single application. Most major ERP vendors such as SAP and Oracle have SCM modules integrated with their ERP systems.

Figure 2-4 shows the five waves of the ERP movement (Sammon and Adam 2005). The 1970s saw the emergence of the production oriented information system, MRP. The MRP in Wave 1 tried to automate all aspects of production master scheduling and provided more control on the inventory planning. In the 1980s, the close-loop and extended version of MRP, MRP II, was developed to focus on production capacity limitations and other business functions, including order processing, manufacturing and distribution. MRP II was improved and renamed as ERP by integrating the isolated manufacturing systems and related data and processes within the organization. In Wave 2, i.e. enterprise integration in the 1990s, ERP embraced functions across the organization such as finance, human resource management and payroll, demand, inventory control, distribution, quality control, etc. The information from these varying functions and systems had been integrated and shared within the organization to improve the efficiency and facilitate the process standardization across multiple business units. In Wave 3, i.e. customer-centric integration starting from late 1990s, the focus of ERP's business requirements had been shifted from cost cutting, efficiency and internal visibility to customer value and customer service. This was achieved by further expanding ERP functions to include sales, marketing and e-commerce. Different from traditional ERP solutions that support make-to-stock and configure-to-order, the customer-centric resource planning (CRP) meets the business requirement of build-to-order and fulfil-to-order (Kalakota and Robinson 2001). The development of extended resource planning (XRP) in Wave 4, i.e. inter-enterprise integration extends the scope of ERP system to cover the entire value chain, which includes customers, suppliers and trading partners of an enterprise. By the integration of external and internal business activities and better synchronization with trading partners, XRP is able to pull up-to-date data from every step of the supply chain and internal organization and provides intelligent decision support capacity so as to reduce inventories

and cycle times, foster competitive pricing strategic, and increase customer service level and customer satisfaction throughout the entire supply chain of the enterprise. The web-centric model of ERP II in Wave 5 further allows the system to be accessed real-time by both employees of the organization and external resources of its supply chain such as suppliers and customers. Especially, ERP II has embraced customer relationship management (CRM) and SCM functionalities in addition to being web and WAP enabled (Suresh *et al.* 2010).

Figure 2 - 4 The five waves of the ERP movement (Sammon and Adam 2005)

2.1.2 ICT and Supply Chain Management

In a supply chain, information technologies support internal operations, and also the coordination and collaboration between supply chain partners. It relies on high speed networks, various databases and information systems for data sharing and better management of the supply chain as a whole in order to achieve competitive values (Hugos 2006). Data capture and data communication can be realized through the Internet, the mobile network, the broadband and related communication protocols. Data storage and retrieval can be accomplished by database management systems, such as SQL Server from Microsoft, MySQL from Sun Microsystems and DB2 from IBM. Information systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), forecast and demand management system, Advanced Planning and scheduling (APS) and Manufacturing Executive System (MES) are developed and deployed to manipulate the data through transactions or simple/complex data processing and generate the necessary reports.

As mentioned in Section 2.1.1, information and communication technologies (ICT), which brings about e-business, has created much impact on almost every sector of the society. The on-going of e-business has advanced the application of supply chain management (SCM) to e-manufacturing and brings about global manufacturing. Conversely, recent review shows that global manufacturing has increased the complexity of SCM, and as a result, supply chain coordination and optimization have become essential elements of manufacturing strategy. The so-called e-business enabled supply chain, or e-supply chain management, is an on-going manufacturing and business strategy that enables the power of e-business to be integrated with manufacturing operations and various supply chain units through the application of the Internet, mobile and other tether-free technologies. The e-business uses the Internet, ICT and digital technologies to manage business processes internal to the organization and with other businesses (Schniederjans *et al.* 2010). It enables more efficient internal and external data processing which promote the close work relationship between companies and their suppliers/partners. As such, it is able to accelerate product realization, manufacturing and delivery, and results in a shorter product cycle time, lower cost, better response to customer needs and improved customer services. By embracing the e-business, e-supply chain is able to provided better availability of service on the Internet, cost reduction in order and customer information processing, better access to global customer markets and less operating costs.

As mobile technology emerges as the leading individual/personal digital content device, m-business (m-business 2010) that relies on the mobile, wireless technology and personal digital devices including personal digital assistant (PDA), smart phone and PDA phone has created a new value chain that allows supply chain activities to be carried out real-time in a synchronized and instantaneous manner. For example, the mobile real-time supply chain coordination built on top of the m-business (Soroor *et al.* 2009) enables the instant order and customer data processing. Through searching an e-market registry and the coordination of agents representing different services, the contractual details are agreed and the order is

processed and shipped by the supplier.

Figure 2 - 5 Structure of pyramid supply chain (Ghayur 2003)

Figure 2 - 6 Structure of hour glass supply chain (Ghayur 2003)

Furthermore, supply chain structures have been developed in the context of e-supply chain. Ghayur (2003) discussed two types of e-supply chain structure, Pyramid Supply Chain (PSC) and Hour Glass Supply Chain (HGSC). In PSC, the MNC is at the top of the supply chain. It creates the orders to assemblers which request the components from manufacturers who connect to their suppliers for materials (Figure 2-5). Compared to traditional companies, companies on PSC have such advantages as shorter production cycle time, fewer layers of sales and fewer and nearly fixed suppliers. The biggest problem of the PSC is the total dependency of the entire chain on one MNC company. The HGSC (Figure 2-6) on the other

hand structures the customers on the top and grassroots suppliers at the bottom. It provides a platform “on which every entity in an economy can join and transact, using Internet technology” (Ghayur 2003).

Globalization is forcing companies and their entire supply chain to be more flexible, scalable and responsive but less costly modes of operation. Companies have to leverage on new information technologies and systems to achieve overall supply chain improvements. For example, business intelligence systems continuously evolve. This helps companies to better understand the happenings within their own organizations, along the whole supply chain, and within the markets they serve (Hugos 2006) by data collection and analysis; Radio Frequency Identification (RFID), which has been widely used in tracking and tracing systems in recent years (He et al. 2008), is one of the enabling technologies that allows the identification of objects in a fully automated manner via radio waves; There are strong interests of companies emphasizing more environmentally-friendly supply chains, green sustainable supply chain, that tries to maximize the resource efficiency, eliminate the waste, and promote the reuse or recycle of the by-product and product at the end of its life cycle to deal with the resource depletion and the environmental change (Dale 2010, Webber and Wallace 2009).

2.1.3 Outsourcing

As mentioned in Section 1.1, today’s enterprise such as Ford is constantly examining its internal processes and their performances. The non-core competency functions and services are eventually eliminated and contracted out in order to free up resources and reduce the cost. Besides, through outsourcing, the enterprise is able to gain effectiveness by focusing more on its own competencies. Different types of outsourcing such as business process outsourcing to outsource the entire department or process of an enterprise and value-added outsourcing to combine both parties’ strengths to market product and service have been summarized by Schniederjans *et al.* (2010).

Enabled by globalization, the advancement of ICT and the e-business, outsourcing is changing its roles in business organizations. In the past, organizations used subcontracting rather than outsourcing and mostly were domestic outsourcing of tangible products. In present day, big organizations use outsourcing for non-core activities, tangible products and intangible services. They mostly are international outsourcing that involves at least one foreign firm. In the near future, organizations may form virtual organizations with almost everything outsourced. It includes non-critical business activities and large portion of total production and service activities. These activities are mostly in the form of global outsourcing that involves many international and external firms (Schniederjans *et al.* 2010).

The main reason for driving outsourcing activities is the possibility of significant reduction in cost and capital expenditure (Outsourcing 2010, Schniederjans *et al.* 2010). Organization can leverage on outside expertise and technology to improve its core services and products. However, an organization has to understand that there will be less managerial control of the service provider and more security and confidentiality issues. In addition, outsourcing may not be always cheaper. Sometimes it may be more expensive than in-house process.

2.2 Supply Chain Optimization

Realistic supply chains have various modes of transportation and multiple end products with shared components and capacities. The flow of materials is not always along an arborescent network, and sometimes the bill of materials for the end items may be both deep and large. Traditionally, various functional units along a supply chain have their own objectives and operate independently. The objective of marketing strategy to achieve high customer service level and maximize sales may have conflicts with manufacturing and distribution goals of minimizing manufacturing cost and inventory. The individually optimized plan of a single manufacturing plant or any other supply chain unit may incur big loss for the entire supply chain (Fawcett *et al.* 2008, Torabi and Hassini 2009). Thus, there is a need to devise a system

through which these different functions can be integrated. As a consequence, a globally optimized solution is necessary in order to benefit the entire value chain.

In recent years, many researches have attempted to bridge the gap among the various functions of a supply chain through coordination and optimization of the information and materials flow. Some of the supply chain models focused on individual issues such as logistics, inventory levels and variations of customer demands and forecasts while others attempted to provide suggestions for companies to design or restructure their supply chains so as to improve the performance.

Various research areas, including i) supply chain design and analysis (Vidyarthi *et al.* 2009, Wang *et al.* 2005); ii) supply chain coordination (Soroor *et al.* 2009, Xue *et al.* 2005); and iii) location decisions and optimization (Kodali and Routroy 2006, Robinson and Bookbinder 2007); iv) transportation decisions and optimization (Sawadogo and Anciaux 2009, Zhong *et al.* 2008); v) inventory decisions and optimization (Chen *et al.* 2009, Piplani and Fu 2005); vi) tracking and tracing systems (He *et al.* 2008, Fritz and Schiefer 2009, Mousavia *et al.* 2005); and vii) reverse logistics (Lee and Chan 2009, Zhu 2008), have been addressed in many literatures.

2.2.1 Supply Chain Design and Analysis

As the market has become increasingly competitive, competitors will not only compete on product technology but also on the efficiencies of the supply chains. A supply chain needs to acquire the ability to shorten the time-to-market of a product, adjusts to changing consumer needs and delivers a satisfactory customer service level. It must be structured so that the suppliers have an effective means of delivering components and, if required, must be sensitive to lead time as well as quality issues. The design of a supply chain should also promote timely communication with both its customers and suppliers. This will enable the company and its supply chain greater flexibility to react to changes in the market.

Graves *et al.* (1998) modelled a supply chain as a linear single production-inventory system. The system made use of performance measures such as production smoothness, production stability and inventory requirements to evaluate the inventory problem. Specially, they attempted to optimize production capacity and inventory for a single production, and subsequently, extended it to deal with multiple production-inventory problems. They also analysed the influence of forecast and requirement planning of the supply chain on other supply chain units by dynamic modelling. Basically, their model used stationary demand, ignored the internal stock out and simplified the production process.

Some aspects of the design and control of logistical processes for traditional integrated systems, and virtual factories for the sheet metal industry has been discussed in the work of Cser *et al.* (2000). Through manufacturing, factory based logistics had been replaced by global logistic concepts which could be used to determine materials flow, optimize the parameters as well as to evaluate performance.

Using the results obtained from network flow theory, inventory theory and simulation theory, Rao *et al.* (2000) developed an optimization engine for the design of Caterpillar's supply chain. They attempted to address the effects of different factors, such as inventory level and trans-shipment mode on profitability.

Angerhofer and Angelides (2000) conducted a review on system dynamics modelling in supply chain management. They divided their investigation into three parts: i) contributions to theory-building; ii) applications to solving a problem in supply chain management; and iii) methodological contribution to improving modelling approaches. They concluded that current work on system dynamics modelling in supply chain management mainly focused on inventory decision and policy development, demand amplification and supply chain re-engineering and design.

Dong and Chen (2001) presented a set of Computer Integrated Manufacturing Open System

Architecture (CIMOSA)-based process behaviour rules to model the business process routing structures of a typical manufacturing supply chain network. Object-oriented predicate/transition nets based on Petri-nets were proposed for the modelling and analysis of process models. Tukel and Wasti (2001) modelled and analysed the relationship between buyers and suppliers using a so-called resource constrained project scheduling strategies, in order to reduce product development time and improve project performance.

Lakhal *et al.* (2001) proposed a mathematical programming model of an extended enterprise. In their work, activities, resources and products were modelled as a directed multi-graph of activities using resource cost functions and product value functions. Basically, it was a large-scale mixed integer programming (MIP) problem and could be used to investigate strategic networking issues. A heuristic based on commercial software such as CPLEX or ILOG to obtain solutions from the MIP model was also presented. However, such a model was limited to the handling of static supply chain problems. It is important to note that the dynamics of a supply chain need to be taken into account when dealing with strategic issues.

Luo *et al.* (2001) proposed an integrated e-supply chain model for agile and environmentally conscious manufacturing. Their work examined raw materials suppliers, tiers I and II suppliers, end-of-life product collectors and de-manufacturers, and extended performance measures to cover environmental issues. Fuzzy logic was embedded in their multi-objective optimization model. As pointed out by Luo *et al.*, their proposed optimization algorithm was not suitable for large network problems.

The work of Wang *et al.* (2005) looked into the selection of suppliers based on the Supply-Chain Operations Reference (SCOR) model level I performance metrics and developed a so-called supply chain effectiveness measurement that was able to determine how good a supply chain design was. Analytical Hierarchy Process (AHP) and Pre-emptive Goal Programming (PGP) were employed to deal with qualitative and quantitative measures, respectively.

Elmaraghy and Majety (2008) attempted to develop a multi-criteria mixed integer programming optimization model for the selection of suppliers, computation of production quantities and determination of transportation modes. A typical supply chain design problem gleaned from the automobile industry was investigated.

Xu *et al.* (2009) developed a random fuzzy programming model for multi-stage supply chain design. Uncertainties associated with the demand, supply, price and various relevant costs were modelled and dealt with using fuzzy logic. This random fuzzy programming model was subsequently converted into a deterministic 0-1 integer programming model and the optimal solutions were obtained by using a so-called spanning-tree technique which was based on genetic algorithms.

Vidyarthi *et al.* (2009) studied two business strategies: make-to-order (MTO) and assembly-to-order (ATO). They attempted to work out the design of a supply chain by minimizing the response time in addition to the fixed cost of opening distribution centres (DCs) and equipping them with sufficient assembly capacity and the variable cost of serving customers. Both MTO and ATO were modelled as non-linear mixed-integer programming problems. The MTO model was used to determine the location and the capacity of DCs and allocate stochastic customer demand to DCs. It was solved by an approach that was based on a so-called cutting plane method. The ATO model considered factories and DCs serving a set of customers, and solved the supply chain problem by a Lagrangean heuristic.

Hammami *et al.* (2009) attempted to develop a strategic-tactical supply chain design model that integrated all the relevant components characterizing the delocalization problem. The model considered technological issues such as technology selection, technological cost and technological constraints, and supplier selection issues such as supplier selection, supplier integration costs and supplier constraints in addition to capacity acquisition and relocation decisions, and transfer prices determination. They used a branch-and-cut algorithm provided

by a commercial software (CPLEX9.0) and developed a method based on Lagrangian relaxation for large instances

2.2.2 Supply Chain Coordination

As mentioned in Section 2.1, recent developments in global manufacturing have both increased supply chain complexity and reinforced the notion that supply chain coordination and practices are essential elements of business strategy. Thus, many organizations have moved from centralized, vertically integrated, and single-site manufacturing facilities to geographically dispersed networks of resources that collectively create value for customers. These extended enterprises may be consonant with a single multinational organization or, as is increasingly the case, a set of strategically aligned companies to expand their capacity and capture specific market opportunities by forming some kind of business partnership or alliance. They are designed to provide the speed and flexibility necessary to respond rapidly to windows of market opportunity.

Traditional supply chain practices and technologies that integrate productive and logistical activities within a company are necessary but not sufficient for competitive success. New supply chain practices and technologies such as e-business and e-manufacturing, must now link production and logistics processes in different organizations across geographically dispersed locations.

Huiskonen and Pirttila (2002) studied the coordination of activities between two different organizations, which could actually be viewed as an extended enterprise. The objects of analysis were a logistics outsourcing relationship and its inter-organizational coordination requirements. The possibilities of using different forms of lateral coordination mechanisms such as informal coordination, formal inter-organizational teams, and integrating roles had been discussed. They found that the development of lateral organizational capability through practicing the presented lateral coordination mechanisms, and actively promoting it to

customers, could become a potential source of competitive advantage for logistics service providers.

Kalakota *et al.* (2001) developed an agent-based system to provide real-time solutions at planning level. By using mobile agent technology, Gupta *et al.* (2001) suggested an approach, which was based on globally available information, to facilitate supply chain decision making. Dumond and Roche (2000) used a so-called π -calculus to specify multi-agents and addressed their global coordination. As a result, customer requirements could be fulfilled through negotiation and communication of distributed agents while customers, logistics, warehouses, resources and plants were modelled as π -calculus processes. Ito and Salleh (2000) proposed a blackboard architecture to implement a collaborative supply chain system. Agent technology was employed to achieve an effective material flow and to shorten the production lead-time.

In the area of virtual enterprise, Rupp and Ristic (2000) presented a distributed planning methodology for the manufacturing of semiconductors and proposed leaving as much responsibility and expertise as possible to local planning systems for carrying out optimization tasks while maintaining a global coordinating entity to ensure an efficient supply chain. In their work, the solution space for solving the problem seemed to be very large which prolonged the computational time drastically. Furthermore, there was no guarantee of an optimal or a good-enough plan for the entire manufacturing system.

Camarinha-matos and Pantoja-lima (2001) developed PRODNET to support coordination in virtual enterprises. The PRODNET was intended to support a large diversity of enterprises and interconnection modes, ranging from small company to a medium or large company with various legacy systems.

Gaonkar and Viswanadham (2001) considered a global manufacturing system comprising contract manufacturer, logistics provider, and OEM, and examined the influence of sharing scheduling and demand information over the Internet within these organizations. A linear

programming based optimization model for this environment was developed. Stock *et al.* (2000) explored the relationship between enterprise logistics practices and improved the performance of a new global enterprise. In response to competitive pressures, a conceptual framework that explicitly recognized the emerging role of logistics and its importance to new supply chain structures was proposed. Specifically, they examined the alignment of logistics practices and supply chain architectures using the notion of “fit”, which was the consistency between logistics practices and supply chain structures. Using a so-called configurations approach, a set of hypotheses linking the ‘logistics–supply chain fit’ to organizational performance was examined. Their results indicated that enterprise logistics was a necessary tool for the coordination of supply chain operations that were geographically dispersed around the world. However, for a pure network structure, high level enterprise logistics integration alone does not guarantee an improved organizational performance.

Xue *et al.* (2005) presented a multi agent system for supply chain coordination in the construction industry. The proposed system applied utility theory and was able to perform multi-attribute negotiation. Basically, it extended the internal supply chain of a construction company to include external supply chains of designer, subcontractors and suppliers.

Arshinder *et al.* (2007) investigated a “situation–actor–process” (SAP) model as well as a “learning–action–performance” (LAP) model. These models were applied to analyze the status of coordination in the supply chain of a leading automotive parts manufacturer in India. The various issues under investigation included coordination with suppliers, coordination with buyers, information sharing, information system, coordination initiatives and flexibility to coordinate with members.

2.2.3 Transportation Decisions and Optimization

In the real world, many logistics problems cannot be simply defined as a transportation problem. They are closely linked to inventory management, since the best choice of mode is

often found by trading-off the cost of a particular mode of transportation with the inventory costs associated with transportation. Though air shipments may be fast, reliable, and warrant lesser inventory level, they are expensive. While shipping by sea or on rail may be much cheaper, they require holding relatively large amounts of inventory to buffer against the inherent uncertainty associated with them. Thus, a good understanding of the influence of the different transportation modes and policies on the entire supply chain can possibly be obtained by analyzing transportation alone, especially when the selection of the modes of transportation is the main issue.

Leung *et al.* (2002) studied a transportation management problem faced by a Hong Kong manufacturer as the company's factory was located at Dongguan of China and the headquarter and distribution centre (DC) in Hong Kong. Three alternatives modes of transportation were discussed: i) using private lorries to transport the products directly from Dongguan to Hong Kong; ii) hiring Hong Kong lorries to transport products directly from Dongguan to Hong Kong; and iii) hiring China lorries to transport products from Dongguan to Shenzhen first and switching to private lorries for the trip between Shenzhen and Hong Kong. Since the transportation cost, the hiring cost, the inventory cost, and the allowance paid to the lorry drivers were different, a mixed integer programming (MIP) model was developed and solved by a software package called Linear Inter-active and Discrete Optimization (LINDO).

Keen competition in the transport market has led to new cooperative arrangements between third-party logistics providers in the form of hub-and-spoke systems (Zapfel and Wasner 2002). As a result, management had to decide whether to adopt a pure hub-and-spoke system, where all the quantities within the transportation network flow over the hub from or to the depots, or a hybrid hub-and-spoke network in which direct transports took place. Mathematical models for these operative planning tasks were developed and applied to an Austrian parcel service provider and the problem was solved by heuristic method which

combines expert rules with local search.

A dynamic assignment strategy, which allowed exchanging components between orders with various priorities and optimizing the logistic processes to minimize the overall delivery delays, was proposed by Sousa *et al.* (2002). Sousa *et al.* applied fuzzy decision making technique to optimize logistic processes. Several criteria for assigning components to orders were also investigated.

Liang (2007 and 2008) presented a fuzzy goal programming approach to deal with fuzzy multiple goals, conflicting objectives and vagueness in the information. The proposed approach was able to simultaneously minimize the total distribution cost, delivery time and production costs.

Zhong *et al.* (2008) suggested a framework called PECAS, i.e. Production, Exchange, Commodity Allocation System. PECAS has three modules, namely activity allocation, space development and transport supply. The study showed that the flows of all commodities, including goods, service, space, land and labour could be simultaneously considered.

2.2.4 Location Decisions and Optimization

The geographic placement of production facilities, stocking points, and sourcing points is critical to a supply chain. The location of facilities affects the commitment of resources. Once the size, number, and location are determined, so are the paths by which the materials and product flows through suppliers to the final customer. These decisions are of great significance to a company since they represent the basic strategy for accessing suppliers and customer markets, and have a considerable impact on the revenue, cost and level of service. Thus, they should be determined by an optimization approach that takes into account production costs, supplier availability, inbound and outbound logistics, distribution channel and costs and customer markets

Jayaraman and Pirkul (2001) studied an integrated logistics model for location production

and distribution facilities in a multi-echelon environment. A mixed integer programming (MIP) formulation had been developed to represent the integrated logistics model. This allows the performance of the integrated logistics model to be evaluated.

Hwang (2002) examined the possibility of optimizing the performance of a supply chain with respect to required service levels in terms of the number of warehouses or distribution centres (W/D) and vehicle routing schedule. In his work, a supply chain comprised plants, W/D and customers. Firstly, the problem was formulated using a so-called stochastic set-covering technique to determine the minimum number of W/D centres among a discrete set of location sites so that the probability of each customer to be covered was no less than a critical service level. Subsequently, the problem was solved using the '0-1' programming method. Finally, a vehicle routing problem was formulated using an improved genetic algorithm.

Kodali and Routroy (2006) presented a four-phase decision making framework for the selection of facilities in a supply chain. The four phases were i) supply chain strategy review; ii) selection of feasible locations; iii) analysis of feasible locations based on qualitative measurements and cost analysis; and iv) ranking the desirable locations and choosing the best location based on benefit/cost ratio. An analytical hierarchy process (AHP) was developed for qualitative analysis and for solving the multi-criteria problem. Viswanadham and Kameshwaran (2007) developed a generic decision making framework to facilitate the location selection process in global supply chains. A hierarchical structure with four fundamental criteria, namely product/process value chain, economic and political integration, resources and management, and enabling technologies, was proposed.

Robinson and Bookbinder (2007) formulated a mixed-integer programming model to optimize the number and location of finishing plants and distribution centres, each from a discrete set of alternatives, as well as to specify the flow on arcs and the transport mode employed, while minimizing the total cost and satisfying each customer's demand over a

multi-period time horizon. The MIP model was solved using some optimization software.

Melo *et al.* (2009) presented a review on facility location analysis within the context of SCM. The general relationship between facility location models and strategic supply chain planning was discussed. Supply chain performance measures, solution methodologies as well as applications of facility location models to strategic supply chain planning were also analyzed.

2.2.5 Inventory Decisions and Optimization

In a supply chain, goods are produced, stored, and then delivered based on demand or forecast. Inventories exist at every stage of the supply chain as either raw materials, semi-finished or finished products. They can also be “in-process” between locations. The primary purpose is to buffer against any uncertainty that might exist in a supply chain. Since holding of inventories is costly, efficient management is therefore critical to supply chain operations. Researchers examined various strategies, such as push and pull, to determine the optimal level of order quantities, safety stocks, and reorder approaches and points, at each inventory location. These decisions are crucial for providing the necessary level of service level to the customers.

Geunes and Zeng (2001) investigated the impacts of inventory shortage policies had on transportation costs in a two-stage distribution system under uncertain demand. They proposed a model that provided an insight into the relationship between inventory decisions and transportation costs. The model could be used to support delivery policy negotiations between a supplier and a customer.

Baganha and Cohen (1998) presented a hierarchical framework to analyse stabilizing effects of inventory in multi-echelon manufacturing/distribution supply chains. They considered retailer and distribution centre in their framework and show how the optimal behaviour of companies could stabilize inventories. They found that variance amplification does not necessarily exist throughout a supply chain. An approach based on multi-echelon

decomposition was used for the analysis. Ettl *et al.* (2000) assumed capacity is infinite and developed a supply network model to minimize the overall inventory capital throughout the network. They attempted to guarantee customer service requirements by generating the base-stock level at each store and the stocking location for a part or for an end-product while considering on-hand inventory (finished goods) and WIP with non-stationary demands. Viswanathan and Piplani (2001) modelled a one-vendor, multi-buyer supply chain for a single product. The benefit of coordinating supply chain inventories through the use of common replenishment time periods was analyzed.

Piplani and Fu (2005) presented a coordination framework known as ASCEND to align inventory decisions in decentralized supply chains. Multi-agent technology was used to delegate different tasks such as coordination, planning and execution. A genetic algorithm-based coordination process was employed to optimize the combination of fill rates and the optimal performance measurement schema for the supply chain.

Feng and Wang (2008) proposed a real-time inventory-routing integrated model to analyze dynamic location and time information in a mobile supply chain. In order to reduce the cost and keep an acceptable service level, a constraint-based genetic algorithm approach to resolving the NP problem and satisfying complex constraints was proposed. It was able to dynamically optimize the destination and quantity of on-the-way inventory.

Seliaman and Ahmad (2008) considered a three-stage supply chain system involving suppliers, manufactures and retailers. They assumed production and inventory decisions were made at supplier and manufacturer levels and the demand at each end retailer was stochastic. A direct search program based on the Hooke and Jeeves method was developed to find the optimal solution under two coordination mechanisms, called equal cycle time mechanism and integer multipliers mechanism.

Chen *et al.* (2009) developed an inventory decision system based on intelligent agent and

artificial neural network. The system took into consideration the impact of the total supply chain cost. The effects of decision making on factory, wholesaler, distributor and retailer were also studied.

2.2.6 Tracking and Tracing Systems

Transport and logistic today have evolved into a high-technology industry. Distribution is no longer about moving cargo on road or via air from A to B, but is a complex process that adopts intelligent systems for sorting, planning, routing, and consolidation. Many large companies have developed solutions to deliver these services in order to meet the requirements of their customers and to improve their services.

Radio Frequency Identification (RFID) is one of the enabling technologies that allows the identification of objects in a fully automated manner via radio waves. It has been widely used in tracking and tracing systems in recent years. Wang *et al.* (2007) used RFID technology to improve the efficiency of tracking tires, warehouse management and extended it to deal with aftermarket compensation management. Gandino *et al.* (2007) described how RFID could be properly used to improve a tracing system in the agri-food supply chain. He *et al.* (2008) attempted to develop a secure RFID-based tracking and tracing solution for supply chain applications and implementations.

2.2.7 Reverse Logistics

In a competitive business environment, it is critical for companies to channel their energies and core competence to realize an efficient and effective forward supply chain. However, after selling their products to distributors, major retail chain stores, or consumers directly, their supply chain process does not stop there. Reverse logistic management is not an easy task. It involves multiple parties and complex tasks.

Companies eventually are forced to face enormous amount of problems related to reverse logistic management. In the United States, companies such as Xerox, Home Depot and

Eastman Kodak have successfully adopted third-party logistics providers to handle the returns of retail business (Wang and Zhang 2009). Statistics showed that 80% – 90% of the returns of retail business have been efficiently managed by the third-party logistics providers through re-producing and optimizing the reverse process and information system.

2.3 Supply-Chain Operations Reference (SCOR) Model

It is noted that most of the researchers mentioned in Section 2.2 developed their own supply chain models and used them as the basis of their heuristic approaches. These supply chain models are not able to provide a common supply-chain framework and standard terminology. Hence, they cannot be used as a generic model for evaluating, and implementing supply-chain applications. Furthermore, they are difficult to be reused and adapted to other companies or industries due to lacks in flexibility and scalability. In order to address the above, the Supply-Chain Operations Reference (SCOR) model proposed by the Supply-Chain Council is reviewed and presented in this section.

2.3.1 An Overview of the SCOR Model

The Supply-Chain Council was organized in 1996 by Pittiglio Rabin Todd & McGrath (PRTM) and AMR Research. Currently, it has over 700 members world-wide, many of them are large manufacturers, including Intel and Siemens (Supply-Chain Council 2009).

Basically, the SCOR model aims at providing a set of standard supply chain practices to create reusable and comprehensive procedures. It offers practices procedures for a wide variety of supply chain activities, such as the planning, sourcing and delivery of goods, spanning from the supplier to the manufacturer to the end customer, which can describe supply chains that are very simple or very complex using a common set of definitions. The latest SCOR is version 9.0. In a nutshell, the SCOR model involves (Supply-Chain Council 2009):

- All customer interactions, from order entry to paid invoice;
- All product (physical material and service) transactions, from the supplier's supplier to the customer's customer, including equipment, supplies, spare parts, bulk products, software and etc;
- All market interactions, from the understanding of aggregate demand to the fulfilment of each order.

2.3.2 Processes in SCOR Model

The SCOR model has five distinct management processes of a supply chain, namely Plan, Source, Make, Deliver and Return (Supply-Chain Council 2009).

- (1) Plan: to balance the aggregate demand and supply to develop a course of action which best meets sourcing, production and delivery requirement.
- (2) Source: to procure goods and services to meet planned or actual demand.
- (3) Make: make-to-stock, make-to-order, and engineer-to-order production execution to transform product to a finished state to meet planned or actual demand.
- (4) Deliver: to provide finished goods and services to meet planned or actual demand, typically including order management, transportation management, distribution management and warehouse management.
- (5) Return: associated with returning of raw material to supplier or receiving returned products, including defective products, MRO (Maintenance, Repair and Overhaul) products, and excess products, from customer for any reason. These processes extend into post-delivery customer support.

SCOR must accurately reflect how a supply-chain's configuration impacts management processes and practices. Each basic supply-chain is a "chain" of Source, Make, and Deliver execution processes. The intersection of two execution processes (Source-Make-Deliver) is a "link" in the supply-chain.

- Execution processes transform or transport materials and/or products.
- Each process is a customer of the previous process and a supplier to the next.

Planning processes manage these customer-supplier links.

- Planning processes thus “balance” the supply chain.
- Every link requires an occurrence of a plan process category.

2.3.3 Process Types of SCOR Process

Each SCOR process can be further described by process type. Three process types have been defined (Supply-Chain Council 2009). They are planning, execution and enable.

- (1) Planning: a process that aligns expected resources to meet expected demand requirements.
- (2) Execution: a process triggered by planned or actual demand that changes the state of material goods.
- (3) Enable: a process that prepares, maintains, or manages information or relationships on which planning and execution processes rely.

2.4 Discussion on Agile and Responsive Extended Supply Chain Coordination and Optimization

In order to better understand and compare the literatures on supply chain optimization reviewed so far, a comparison of the various works are summarized in Tables 2-2 to 2-6.

It can be seen from Tables 2-2 to 2-6 that much work has been done in supply chain design, restructuring and functional optimization, such as optimization of the locations of facilities, transportation and inventory, in order to bridge the gap among various functions of a supply chain and the gap between theory and practice. Furthermore, most of the researchers focused on strategic issues such as i) which internal activities should be preserved and developed; ii) what is the relationship among demand, inventory level and customer service level; and iii) how to restructure a supply chain to maximize its profit. The operational issues, which are fundamental to supply chain management, are not well addressed.

Table 2 - 2 Summary of literature review on supply chain design and analysis

References	Descriptions	Solution Approach
Graves <i>et al.</i> 1998	Optimization of the production capacity and inventory while considering the requirement planning to analyze how the forecast will affect other units of the supply chain.	Linear system with Monte Carlo simulation.
Rao <i>et al.</i> 2000	Design of a supply chain.	Network flow theory, inventory theory and simulation theory.
Dong and Chen 2001	Modelling and Analysis of the business processes of a typical manufacturing supply chain network.	Predicate/transition nets based on Petri nets.
Tukel and Wasti 2001	Modelling of the relationship between buyer and supplier to reduce product development time and improve project performance.	Heuristic rules (resource constrained project scheduling strategies).
Lakhal <i>et al.</i> 2001	Modelling of an extended enterprise with generic activity networking: activity, resources and products were modelled as a directed multi-graph of activities with resource cost functions and product value functions for strategic planning.	Mixed integer programming problem solved by commercial solver such as CPLEX.
Luo <i>et al.</i> 2001	Modelling of an extended e-supply chain that considered raw material supply, tier I and II supply and de-manufacturing.	Fuzzy logic-based multi-objective optimization.
Wang <i>et al.</i> 2005	Analysis and selection of suppliers based on the SCOR model level I performance metrics and a so-called supply chain effectiveness measurement.	AHP and PGP.
Elmaraghy and Majety 2008	Selection of suppliers, determination of production quantities, selection of transportation method and transported quantities in a multi-stage, multi-level supply chain inventory locations/sizes.	Multi-criteria mixed integer programming optimization model.
Xu <i>et al.</i> 2009	Modelling of uncertainties that associated with demand, supply, price and various relevant costs in random fuzzy environment.	Random fuzzy programming model.
Hammami <i>et al.</i> 2009	Modelling and design of a strategic-tactical supply chain design model that integrates all the relevant components that characterize the delocalization problem.	Branch-and-cut algorithm and on Lagrangian relaxation.

2.4.1 Planning, Control and Customer Order Schedule

Traditionally, a company needs to hold sufficient stock to guarantee a desired service level. This is to ensure a safety stock so as to prevent shortage of materials/final products. Essentially, safety stock as a buffer is able to ensure smooth production and customer satisfaction, and to counteract negative impacts from such uncertainties as late delivery of materials from supplier and unexpected increase in demand. The common way of calculating the safety stock is based on demand, process lead time and service level. However, too much safety stock may incur higher inventory carrying cost; while too little safety stock may affect the desired customer service level.

Table 2 - 3 Summary of literature review on supply chain coordination

References	Descriptions	Solution Approach
Huiskonen and Pirttila 2002	Analysis of the logistics outsourcing relationship and its inter-organization coordination.	Lateral coordination mechanisms.
Gupta <i>et al.</i> 2001	Design and analysis of mobile agents for improving supply chain decision making by access to the necessary global information without violating the security.	Mobile agent technology.
Dumond and Roche 2000	Modelling of supply chain management problem using the multi-agent system based on pa-calculus.	Pa-calculus based multi-agent approach.
Ito and Salleh 2000	Modelling of a blackboard-based system to achieve an effective material flow and to shorten the production lead-time.	Blackboard-based negotiation system.
Rupp and Ristic 2000	Analysis of a distributed planning methodology based on local plan optimization under control of a global coordination entity.	Simulated annealing algorithm.
Camarinha-matos and Pantoja-lima 2001	Analysis of a PRODNET approach to support coordination in virtual enterprises.	Workflow-based coordination.
Gaonkar and Viswanadham , 2001	Study of the influence of sharing scheduling and demand information.	Linear programming.
Xue <i>et al.</i> 2005	Study of a multi agent system for supply chain coordination in construction that extended the internal supply chain of general contractor to external supply chain of designer, subcontractors, and suppliers	Multi-agent system.
Arshinder <i>et al.</i> 2007	Application of a SAP-LAP model to an automotive parts manufacturer to analyze the status of coordination in the supply chain	SAP-LAP model.
Soroor <i>et al.</i> 2009	Study of the basic concepts of mobile real-time supply chain coordination and a framework was proposed.	Mobile and internet technology.

Table 2 - 4 Summary of literature review on transportation decisions and optimization

References	Descriptions	Solution Approach
Leung <i>et al.</i> 2002	Analysis of the model to solve a transportation management problem by selection of proper transportation mode and routing.	MIP problem solved by a software package called LINDO.
Zapfel and Wasner 2002	Analysis of a logistical management problem to select the mode of transportation from pure hub-and-spoke and hybrid hub-and-spoke.	MIP problem solved by heuristic method combining expert rules with local search.
Sousa <i>et al.</i> 2002	Optimization of logistic processes in order to minimize the overall delivery delays while considering order priority.	Fuzzy decision making algorithm and simulation.
Liang 2007 and 2008)	Optimization of the total distribution cost and delivery time by considering some environmental coefficients.	Fuzzy goal programming approach.
Sawadogo and Anciaux 2009	Selection of best route while considering green supply chain by considering environmental aspects such as noise pollution, air pollution, energy consumption.	Multi-criteria decision making problem solved by ELECTRE.

Table 2 - 5 Summary of literature review on location decisions and optimization

References	Descriptions	Solution Approach
Jayaraman and Pirkul 2001	Optimization of location of production and distribution facilities in a multi-echelon environment.	Heuristic method for the MIP problem.
Hwang 2002	Design of a logistical system to optimize the number of warehouses, DCs and vehicle routing schedule.	Appropriate algorithm, clustering, and GA..
Kodali and Routroy 2006	Facility location optimization based on a four-phase decision framework.	Heuristics and AHP.
Viswanadham and Kameshwaran 2007	Analysis of a hierarchical structure that considered criteria such as product/process value chain, resource and management for location selection in global supply chain.	Heuristics and AHP.
Robinson and Bookbinder 2007	Optimization of number and location of finishing plants and distribution centres in a supply chain.	Mixed-integer programming model.

Table 2 - 6 Summary of literature review on inventory decisions and optimization

References	Descriptions	Solution Approach
Ettl <i>et al.</i> 2000	Optimization of the inventory capital and the stocking location and guarantee the customer service requirements by considering on-hand inventory and WIP with non-stationary demands.	Conjugate gradient method to optimize the non-linear problem.
Geunes and Zeng 2001	Minimization of the inventory and transportation costs and recommend the stock level while considering uncertain demand.	Simulation and heuristic method.
Piplani and Yonghui 2005	Analysis of a coordination framework to optimize the fill rates and the performance measurement schema for decentralized supply chains.	Multi-agent system and Genetic algorithm.
Feng and Wang 2008	Optimization of the destination and quantity of on-the-way inventory by using a real-time inventory-routing integrated model.	Constraint-based genetic algorithm approach.
Seliaman and Ahmad 2008	Optimization of the production and inventory decision based on a tree stage supply chain system.	A direct search program based on Hooke and Jeeves.
Chen <i>et al.</i> 2009	Analysis of an inventory decision system that considered the impact factors of the total supply chain cost.	Intelligent agent and artificial neural network.

Many companies such as Dell have decided not to carry large inventory (Dell 2010). They receive orders from the clients; buy components from external suppliers; collect the components in special places as virtual stocks; and assemble and then deliver the orders to the clients. The manufacturing of goods and their distribution to clients in this manner pose a challenge, which is how to deliver the goods in time while minimizing the inventories, reducing the production cost and achieving certain customer service level. Their impact on the overall responsiveness of a large-scale supply chain usually cannot be addressed effectively by simply considering capacity planning of the supply chain and manufacturing

plants without a powerful supply chain planning, control and scheduling system. Any variation in the local plan and the schedule of a supply chain unit such as manufacturing plant might adversely affect the overall performance of the supply chain. This shows the necessity of introducing a mechanism that can better use the e-business information flow network to share production plan and the detailed schedule of the entire supply chain, and allowing each supply chain unit to collaborate instead of trying to optimize individual processes at every stage.

Furthermore, the works of Luber (1991) and Mentzer (2001) revealed that lead-time could be used to estimate the processing time and transition time of a supply chain. To the best of the author's knowledge, most of the work surveyed thus far does not have the ability to estimate the actual loading of a manufacturing plant. As a result, the lead-time assigned is usually much longer than necessary in practice so as to be safe. This may result in higher inventory level and cost. Thus, it is obvious that adopting a holistic approach to planning and scheduling are becoming more and more important for the purpose of achieving a near optimized and well coordinated supply chain. Generally, production facilities are more complex than other units of a supply chain in terms of resources constraints, dynamic of production, uncertainty and so on. For example, sharing of the information about resource constraints of production facilities will facilitate the planning and scheduling of other supply chain units and creates greater values to these supply chain units. In this respect, a generic model that supports hierarchical coordination and optimization of the entire supply chain, as well as a holistic approach to facilitate the integration of detailed scheduling and planning with supply chain management becomes essential to provide accurate schedule and delivery information. It would help in meeting the customer service level, and ultimately achieving strategic goals, such as JIT and capturing market.

From the review, it appears that not many studies have been done to integrate scheduling with supply chain optimization. Griffiths and Margetts (2000) used some case studies to

demonstrate how variations in production schedule could affect the supply of parts and show the importance of supply chain management. Lendermann *et al.* (2001) described a framework for distributed simulation with integrated advanced planning and scheduling (APS) procedures to support a leaner and more responsive supply chain. They illustrated the necessities of integrating APS with supply chain simulation by analyzing the problems faced by some simulation systems without the support of an APS system. It is apparent from their work that detailed schedule is important to supply chain management and optimization.

Reis *et al.* (2001) presented a multi-agent cooperative scheduling system for an extended enterprise comprising capacity agent, retail agent and raw-material agent. The system embodied a dynamic production scheduler. It had a mechanism, which allowed a group of cooperative scheduling agents to work out feasible schedules through physical level and virtual level of coordination among agents, while avoiding only locally feasible solutions. Hence, only one feasible solution is presented to the enterprise. In their work, resource constraints such as tooling were difficult to incorporate due to the restriction imposed by the system developed, which supported single client and single supplier only.

Nurmilaakso (2004) used an agent-based distributed simulation approach to determine some feasible schedules for different companies along a supply chain. Agents that represented companies attempted to resolve the conflicts by exchanging messages about their own schedule. As commented by Nurmilaakso, the approach could not even provide a near optimal local schedule.

Kreipl and Dickersbach (2008) attempted to integrate production scheduling using APO, which is a supply chain planning and scheduling software provided by SAP. Basically, the APO required a plan to be confirmed first. The plan will then be used as the input to individual manufacturing plant for detailed scheduling. During which, coordination among different plants has not been implemented. As a result, a globally optimized schedule is not

achievable.

2.4.2 Supply Chain Model and Representation

From the review, various approaches, including MIP (Elmaraghy and Majety 2008, Jayaraman and Pirkul 2001, Leung *et al.* 2002, Zapfel and Wasner 2002), ‘0-1’ programming (Hwang 2002), Petri nets (Raghavan and Viswanadham 1999), and non-linear model (Ettl *et al.* 2000, Vidyarthi *et al.* 2009), had been used to handle supply chain management problems. They had managed to work out the solutions for these models by using software packages, fuzzy methods, heuristic approaches or even simulations. Functional optimization is of great value to an enterprise since it provides the basic strategy and tactic to assist suppliers and customers, and to ensure sufficient materials or products flow to manufacturing plants in time or to customers with adequate promised customer service level. However, most of the works done so far were for decision-making at management level or were targeted at a specific problem (Leung *et al.* 2002, Vidyarthi *et al.* 2009, Wang *et al.* 2005). Some of the works had been simplified in order to reduce the number of decision variables and to improve the speed of problem-solving. These simplifications included removal of capacity limitation; stationary demand (Graves *et al.* 1998, Elmaraghy and Majety 2008) to simplify production process and eliminate internal stock-out; and a two-stage (inventory-transportation-customer) supply chain (Geunes and Zeng, 2001) that ignored other supply chain units. The SCOR model appears to be suitable as it provides a generic “template” to represent a supply chain and a set of standard supply chain practices to create reusable and comprehensive procedures. It is envisaged that in order to analyze, coordinate and schedule the entire supply chain, a comprehensive representation of a supply chain is fundamental and critical. Such a representation would enable multiple level decision making and optimization, from strategic to operational levels, to take place. It should be able to provide an enabling infrastructure, which is generic, flexible and sophisticated enough to incorporate important supply chain features such as hierarchical structure, various modes of transportation, multiple level split,

merge and assemble, and cross-boundary representation to promote the supply chain coordination and achieve a near global optimized schedule.

2.4.3 Solving Extended Supply Chain Optimization Problems

A supply chain, one that supports global manufacturing in particular, may be enormous in terms of size and number of supply chain units. In reality, an extended supply chain may have multiple end products with shared components, facilities, capacities and suppliers. Thus, the flow of materials is not always along an arborescent network. This will further increase the complexity of the problem.

As mentioned in Section 1.1, an extended supply chain includes supply networks, distribution networks, and alliance networks. It involves everyone who contributes to a product. However, research on how planning and scheduling can be coordinated in order to realize an extended supply chain is lacking. The work on e-supply chain by Luo *et al.* (2001) included tier I and tier II suppliers as well as de-manufacturing. It excluded planning and scheduling of a supply chain and could only be used to handle less complex optimization problems. A network based approach to reduce inventory and improve customer's service level in an n-tier complex distributed supply chain network was discussed by Pan *et al.* (2007). The model only covered the inventory cost and allocation cost. Important factors such as production capacity and transportations had been ignored.

As such, to deal with a sizable supply chain that may grow beyond the ability of existing optimization approaches to cope, a more robust methodology is therefore necessary. It is envisaged that clustering technique, which is capable of decomposing a complex problem into a smaller and controllable ones, would help in reducing the search space and improving the efficiency of the search procedures to derive better solutions for the entire supply chain. In this respect, Group Technology (GT), which was first postulated by Burbidge (1975), can possibly be adapted and used to cluster an extended supply chain. Basically, GT is a

manufacturing technique that can be employed to identify and group together similar parts and manufacturing operations or processes into families during all stages of design and production (Khoo *et al.* 2003, Sneed 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. After the part families are formed, machines are often organized into manufacturing cells and the families of parts assigned to cells according to their routings. It is envisaged that the basic notions of GT can be borrowed and enhanced using such technique as fuzzy clustering theory, graph theory and agent based technology to realize a comprehensive model or representation for the handling of supply chain problems. In so doing, a complex supply chain model can possibly be decomposed into “well coordinated” supply chain clusters comprising supply chain units, transportation modes and work orders.

2.4.4 Intelligent Agent-Based Supply Chain Coordination

From the review on supply chain optimization, planning and scheduling described in Sections 2.2 and 2.3.1, it is apparent that the revision of plans or schedules of supply chain units in a supply chain, which is a frequent occurrence, needs proper coordination. Any slip in the coordination would lead to immediate and tangible losses (Griffiths and Margetts 2000). This implies that the agility with which a supply chain is managed at tactical and operational levels has an impact on the way in which enterprise goals are achieved. Furthermore, the individually optimized solution of a single manufacturing plant or a supply chain unit may turn out to be unfavourable to the global objectives and may even jeopardize the performance of the entire supply chain (Fawcett *et al.* 2008, Infosciler 2003). This provides the motivation for the author to explore and propose an intelligent agent-based decision making mechanism to facilitate the exchange of information and promote negotiation and coordination among the various supply chain units. It is envisaged that such a mechanism would help in realizing a near global optimal schedule for an extended supply chain.

2.5 An Overview of Relevant Methodologies and Algorithms

2.5.1 Group Technology and Fuzzy C-Means Clustering Algorithm

As mentioned, Group Technology (GT) is a manufacturing technique that identifies and groups together similar parts and manufacturing operations or processes during all stages of design and production (Snead 1989). It was first postulated by Burbidge (1975) and provides a useful way to improve the productivity of a manufacturing system. The GT philosophy advocates combining similar parts into a group so that the cost associated with the design and manufacturing the entire group of parts are reduced. Basically, a family of parts is made up of components that can be manufactured by similar machinery, tooling, machine operations, and jigs and fixtures. After part families are formed, machines are often organized into manufacturing cells and the families of parts assigned to the various manufacturing cells according to their routings. Generally, in a manufacturing cell, the set up time to switch from manufacturing one part to another is minimal.

There are four basic methods that can be used to form part families (Bedworth *et al.* 1991, Chu and Hayya 1991, Offodile *et al.* 1994). They are: (i) by visual method, (ii) by parts coding analysis, (iii) by analysing component or production flow, and (iv) by applying optimization algorithms. This work focuses on optimization algorithms, as the first three approaches are difficult to be adapted to handle clustering of supply chains. Common algorithms employed to create manufacturing cells include Rank Order Clustering (King 1980), Direct Clustering (Miltenburg and Montazemi 1993, Mukhopadhyay *et al.* 1994) and Bond Energy (Currie 1992, Suresh and Kaparthi 1994). All of them represent machines (in rows) and parts (in columns) as matrices. More recent techniques include Simulated Annealing (Chen and Srivastava 1994, Souilah 1995, Zolfaghari and Liang 1998), Neural Networks (Lozano *et al.* 1998, Wang and Yoshiyasu 1993) and Genetic Algorithms (Gupta *et al.* 1996, Khoo *et al.* 2003, Rao *et al.* 1999, Venugopal and Narendran 1992).

The effectiveness of cellular manufacturing is often measured the following objectives (Hyer 1991):

- Minimal number of inter-cell movement;
- The greatest proportion of part operations performed within a single cell;
- The greatest number of parts handled by the cells as a percentage of the total number of parts processed through the shop floor;
- Maximum machine utilization;
- Minimal total costs by reducing set-up times and WIP;
- Shortest throughput time of a job; and
- Minimal tardiness of a job.

The extent to which these objectives can be realized depends on several factors, foremost of which are the operating policies such as the dispatching rules and labour utilization, and the way in which machines and parts are grouped into manufacturing cells thereby determining the work load of the machines.

Gupta, *et al.* (1996) made use of Genetic Algorithms (GAs) to perform the grouping of five machines and seven components. Their work aimed at minimizing (i) the total number of inter-cell and intra-cell part movements and (ii) the variation of workload of each machining cell. The inter- and intra-cell part movements were weighted differently. Cell load variation, on the other hand, was given by the difference between the workload of a machine and the workload of the cell. The total movements were formulated as the weighted sum of both inter and intra-cell movement. The GA-based approach was used to determine the machine cell-part grouping. Basically, gross part movement and cell load variation belong to two different domains. It is difficult to use a single equation to represent them as their relative importance is not known and they cannot be simply summed. Gupta, *et al.* (1996) used two distinct populations to evaluate the twin objective functions separately and looked for identical

chromosomes. In so doing, a solution satisfying both problems could be found, although it might not be optimum.

A similar research, based on the same two objectives, was carried out by Venugopal and Narendran (1992). Several real life issues, such as processing time of each part on different machines, and demand of each part and workload on each machine imposed by various parts, were considered. The machine cell-part grouping was determined as a bi-objective problem with 15 machines and 30 parts. The results showed that the GA approach was able to provide satisfactory solutions.

One common weakness with conventional analytical methods and optimizing algorithms based on mathematical models is that the part and machine families are mutually exclusive. Each part can only belong to one part family and each machine to one machine family. However, in reality and in most manufacturing environments, it is possible that the linkages of some parts/machines are less obvious, and human intervention and further analysis have to be performed. Fuzzy clustering is thus a more appropriate technique to deal with machine cell formation problem in a complex real manufacturing environment.

Fuzzy models are good for measuring and expressing the fuzziness in a system. Traditional approaches used in Group Technology (Snead 1989) such as cluster analysis, mathematical programming 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, traditional approaches require re-computation of the entire problem.

The foundation of a fuzzy model is fuzzy theory (Lowen 1996). Fuzzy theory as its name suggests, is basically a theory of classes with blurred boundaries. In a conventional set concept (crisp set), element is either a member of a set or not. Fuzzy sets on the other hand, allow elements to be partially in a set. Each element is given a degree of membership. This

membership value can range from '0' (not an element of the set) to '1' (a member of the set). A membership function expresses the relationship between the values of an element and its degree of membership in a fuzzy set. Fuzzy models are suitable for dealing with impreciseness that may exist in the parameters of a system.

There is a growing research interest in quantifying the fuzziness in part-machine grouping features. A better understanding is therefore needed to choose an appropriate membership function to measure the fuzziness of a process plan and part-machine features. Some fuzzy systems such as the fuzzified version of conventional methods which cover fuzzy c-means clustering (Josien and Liao 2000, Yang *et al.* 2006), and fuzzy rank order clustering (Zhang and Wang 1992), as well as the fuzzified version of modern methods which include fuzzy-neural methods (Kuo *et al.* 2006, Park 2003), have been widely used. For example, Xu and Wang (1989) proposed a simple fuzzy clustering for part family formation. Yang *et al.* (2006) established a fuzzy clustering approach that could take care of mixed-variable for machine cell formation.

2.5.2 Genetic Algorithm Based Fuzzy C-Means

Genetic Algorithm (GA), as described by Holland (1975), is a technique that is easy to apply and can be used to solve a wide range of optimization problems such as scheduling and sequencing (Khoo *et al.* 2000, Mori and Tseng 1997, Qiu 1997), cellular manufacturing (Gupta *et al.* 1996, Li *et al.* 2002, Zhao *et al.* 1996), assembly line optimization (Lee *et al.* 2000), printed circuit board (PCB) layout design (Khoo and Ong 1998), engineering design and concurrent engineering (Carlson 1996, Janikow and St Clair 1995). Basically, GA belongs to a class of techniques called evolutionary computation (Mangano 1995). It is an adaptive search algorithm that operates on a population of individuals representing potential solutions to a given problem. It seeks to produce better or fitter individuals, i.e. solutions, by combining the better of the existing ones through the mechanics of *natural selection* and *genetics*. GA is more robust than traditional search techniques such as guided random-search

or calculus-based techniques for three simple reasons (Goldberg 1989):

- GAs use payoff also known as objective functions rather than derivatives as in the gradient search techniques;
- GAs adopt stochastic transition, not deterministic rules; and
- GA searches are conducted over the entire solution space, not local decision spaces.

Recently, more and more researchers use GA based fuzzy c-means (FCM) to solve different problems. Image segmentation problem (Awad *et al.* 2009; Cheng and Gong 2008; Mukhopadhyay *et al.* 2006), model detection of a distributed sensor networks (Korjani *et al.* 2007), microarray gene expression data clustering (Mukhopadhyay and Maulik 2009), and data mining (Yan and Li, 2008) are some of them. There are also studies on GA based fuzzy c-means in GT (Li *et al.* 2002, Zhao *et al.* 1996). However, the number of cluster centres and the weighting exponent have to be predetermined for the fuzzy c-means approach.

Pang *et al.* (2007) attempted to obtain an optimal solution by solving the fuzzy c-means problem for each value of c ranging from 2 to n (number of samples) in order to search for the best clustering. The approach obviously needs large computation efforts and is time-consuming. Mukhopadhyay and Maulik (2009) and Saha *et al.* (2009) used a GA based fuzzy clustering technique with a variable chromosome to determine the proper number of clusters. A so-called XB index was used as the objective function. However, it is important to note that the XB index is mainly used to determine the number of clusters. It is obvious from the above discussion that c , the number of cluster centres, and m , weighting exponent, may not be known as a prior knowledge and, as a result, have to be predetermined for a fuzzy c-means approach. In this work, the author attempts to realize an approach that is able to search for the optimal c and m while performing optimization.

It is envisaged that genetic algorithms (GAs) and tabu search (TS) can possibly be used to enhance the fuzzy c-means clustering approach. Basically, the tabu search algorithm was

developed by Glover and Hansen (Glover and Laguna 1997, Pham and Karaboga 2000) for solving combinatorial optimization problems. It is an iterative search that is able to help overcome premature convergence by using a flexible memory or a tabu list and search beyond the local minima. Such a hybrid heuristic, i.e. combining GA, TS and FCM, can be used to handle large-scale supply chain clustering problem and at the same time search for the best fuzzy c-means parameters, c and m . Besides determining the cluster in which a supply chain unit belongs to, it is able to provide the degree of membership of a supply chain unit to each of the cluster. This information can help decision makers to decide the final supply chain clusters while considering other constraints such as balancing the workload among clusters and customer preference of manufacturing plants.

2.5.3 Schema Theorem of Genetic Algorithms

The building block hypothesis and the schema theorem (Holland 1975, Goldberg 1989) are fundamental to Genetic Algorithms (GAs). They describe the survival and propagation of schemas from one generation to another and were traditionally used to evaluate the effectiveness of GAs. They postulated that the schemas with long defining length were likely to be destroyed by crossover and short, lower order and highly fit schemas with above average fitness survived and got copies at exponentially increasing rates.

However, the schema theorem has been widely criticised as it only provides the lower boundary instead of the expected exact number of schemas in the next generation (Stephens and Waelbroeck 1998, Stephens and Waelbroeck 1999, Whitley 2001). Stephens and Waelbroeck (1999) even commented that there was no preference for short, low-order schemas and in fact typically “long” schemas would be favoured when schema reconstruction dominated.

Rabinovich and Wigderson (1991) analysed a simple GA dynamics in terms of the fitness distributions. They attempted to develop a more rigorous understanding of how GAs evolve

and create an exact mathematical analysis using a simple GA.

The notion of effective fitness had been introduced by Stephens and Waelbroeck (1999) in governing the reproductive success of a schema. They found that effective fitness appeared to be a more relevant concept than conventional fitness. They further analysed the schema theorem and the building block hypothesis based on the exact evolution equation they proposed in terms of effective fitness for GAs.

Poli (2001) proposed an exact formulation in terms of microscopic quantities to derive the expected number of copies of a schema in the next generation of a GA operation. The formulation was further improved to form a schema theorem for genetic programming (GP). Such a schema theorem supported the calculation of effective fitness in GP. Poli also concluded in his review of GP and GA schemas, and found that the schema theorem was as important as any other mathematical models such as Vose's and Markov models. However, his work was limited to one-point crossover and the effect of mutation was not considered.

Whitley (2001) reviewed and critiqued the schema theorem. An exact version of the schema theorem that considered reproduction, crossover and mutation was proposed using such terminology as "gains", "losses" and "disruptions". The final version of his equation was simplified to provide only the lower-bound of the expected value of the number of instances of a schema in the next generation, while the gains of crossover were ignored.

Ming and Wang (2006) proposed a so-called ternary representation that was able to depict the survival and construction probabilities of a schema. They further discussed a schema survival and construction theory for one-point crossover using the ternary representation.

A stochastic schema theorem within the framework of the Wright-Fisher model of Markov processes was proposed by Zhang *et al.* (2008) to analyse the evolution of the first order schemas with finite population size. The influence of population size and mutation probability on the success probability of obtaining the near optimal solution was studied.

They concluded that when the population size was large, mutation tended to have a negative effect on the fitness of the population, and vice versa.

Basically, the main GA parameters are population size, crossover probability and mutation probability. They are very important to the performance of GAs. A set of good GA parameters helps in improving the ability of the GA to search for near global optimal solutions. However, as the mathematical foundation of GAs is weak, deterministic method for the selection of GA parameters does not exist. Pham and Karaboga (2000) further suggested that as two important control parameters, crossover and mutation probabilities affected the performance of GAs drastically. In practice, it usually takes a lot of trial-and-error attempts to find a set of good GA parameters in order to obtain near optimal solutions. Furthermore, a good set of GA parameters that works well for one problem may not be as effective for other problems. Thus, it is envisaged that an exact schema theorem which extends Goldberg's work can be used to mathematically characterize the evolution of a population of a genetic algorithm. Based on the change in the expected number of schemas over GA evolution, the optimal or a compromised pair of crossover and mutation probabilities that can possibly lead to a better performance of GA can possibly be obtained.

2.6 Research Roadmap

From the review, seven stages of research have been identified in order to establish the prototype SCASO system: i) a graph-based supply chain representation scheme and hierarchical modelling of supply chains; ii) a framework of a multiple populations search strategy based evolutionary approach (MBEA); iii) an exact schema theorem for GAs; iv) supply chain routing and sequence optimization; v) supply chain virtual clustering; vi) supply chain order scheduling; and vii) a case study to illustrate the prototype system developed.

As mentioned in Chapter 1, the objective of the research is to conduct an investigation into the realization of a hierarchical model and a framework for extended supply chain

coordination and optimization, which would be used as a tool to facilitate the planning and detailed scheduling of the various supply chain units, such as suppliers, manufacturing plants, warehouses, and distribution centres, and provides the capability to support an extended supply chain and global manufacturing, which take into consideration suppliers' and customers' supply chain networks. The research roadmap is summarized in Figure 2-7. It involves

Figure 2 - 7 A research roadmap

- (1) A study on a framework for supply chain optimization, which supports the hierarchical coordination and optimization of the entire supply chain (Yin and Khoo 2007b). This would involve the adaptation of the SCOR model to represent a typical supply chain;

- (2) A study on a framework of the proposed multiple populations search strategy based evolutionary approach (MBEA). The MBEA is a generic optimization methodology and can be employed to solve different optimization problems;
- (3) A study on a novel graph representation of an extended supply chain (Khoo and Yin 2003). This includes i) the representation method; and ii) the logical relationship among nodes of the graph. The graph representation would provide the foundation for supply chain optimization;
- (4) A study on an exact schema theorem which extends Goldberg's schema theorem. It would be able to predict the expected number of copies of schemas in the next GA generation. Further investigation leveraging on the exact schema theorem would be conducted to examine the optimal or a compromised pair of crossover and mutation probabilities that can lead to a better performance of GA;
- (5) An investigation into work order routing selection and sequence optimization (Yin and Khoo 2007a). This would involve the realization of a more robust optimization technique based on local search algorithms such as GA and TS;
- (6) The establishment of a virtual clustering methodology (Khoo and Yin 2003). The basic notions of GT are adapted and enhanced using such techniques as fuzzy c-means, GA and TS. This is used to reduce the search space for the optimization of a complex extended supply chain;
- (7) An investigation into an intelligent agent based mechanism for information exchange and coordination. With the help of a scheduling engine, the mechanism is capable to facilitate and promote the negotiation and coordination among supply chain units to realize global optimization of the schedule for the entire supply chain; and
- (8) Development of a prototype system to illustrate the proposed framework, approaches and algorithms. The effectiveness of the prototype system will be demonstrated by a case study gleaned from a semiconductor packaging company.

2.7 Summary

This chapter presents an overview of supply chain management and optimization. Researches

on supply chain management and optimization have been reviewed and grouped into seven areas: i) supply chain design and analysis; ii) supply chain coordination; iii) location decisions and optimization; iv) transportation decisions and optimization; v) inventory decisions and optimization; vi) tracking and tracing systems; and vii) reverse logistics.

The necessity of a mechanism that is able to facilitate an agile and responsive supply chain coordination and optimization has been discussed. Though much work has been done in supply chain design, restructuring and functional optimization, operational issues, which are fundamental to a supply chain management, are not well addressed. It is noted that variation in the local plan and schedule of a supply chain unit may adversely affect the overall performance of the supply chain. The review also reveals that the widely used lead-time approach may result in higher inventory level and cost. Furthermore, sharing of the information on resource constraints of production facilities can possibly facilitate the planning and scheduling and creates greater values to other supply chain units. In order to provide a reasonably good schedule and delivery information, i) a comprehensive representation such as graph representation, ii) a generic model supporting the hierarchical coordination and optimization of the entire supply chain, and iii) an approach to facilitate the scheduling and planning for supply chain management appear to be essential.

In order to deal with a sizable supply chain that may grow beyond the ability of existing optimization approaches, it is envisaged that clustering and agent based technology would help in reducing the search space and improving the search for better solution.

Finally, a discussion on the key methodologies and algorithms that are relevant to this work has been presented. They are group technology (GT), fuzzy c-means, genetic algorithm (GA), tabu search (TS) and the Schema Theorem. It is envisaged that the basic notions of GT can be borrowed and enhanced using fuzzy c-means, GA and TS. The enhanced GT allows a complex extended supply chain model to be decomposed into supply chain clusters of smaller

size. In doing so, the search space of a complex supply chain problem can be drastically reduced and the efficiency of the supply chain optimization can possibly be improved. Furthermore, it has been established that the crossover and mutation probabilities of a GA can drastically affect the performance of GA. An attempt to enhance Goldberg's schema theorem will be explored. With the enhancement, it is envisaged that important parameters for fuzzy clustering of supply chains as well as for GA can be obtained. As a result, a prototype system to facilitate supply chain coordination and optimization can possibly be realized.

Chapter 3 A DISTRIBUTED HIERARCHICAL MODEL AND A FRAMEWORK FOR SUPPLY CHAIN COORDINATION AND OPTIMIZATION

3.1 Introduction

As mentioned in Chapter 2, a distributed hierarchical model of a supply chain is fundamental and critical to provide an enabling infrastructure for extended supply chain coordination and optimization. It needs to be generic, flexible and sophisticated enough to allow the incorporation of important supply chain features so as to promote supply chain coordination and derive a near global optimized schedule. In this chapter, a framework for supply chain optimization, which supports the hierarchical coordination and optimization of an entire supply chain, is proposed.

Figure 3 - 1 Different level of supply chain management

As shown in Figure 3-1, supply chain optimization and management have different levels. The strategic and long term level includes decisions on supply chain design and configuration, and location of facilities. It is designed for long term application and is relatively expensive

to change. The time frame of the tactical level is about a quarter to 12 months. It works on forecast and demand, capacity planning, and inventory policies. The operational and short-term level deals with customer orders and production scheduling in daily or weekly basis (Chopra and Peter 2004). As mentioned in Chapter 2, the integration of scheduling with supply chain optimization is a difficult task. The necessity of carrying out such a task includes

- Long-term management objectives frequently conflict with operational objectives. For example, manufacturing operations may try to maximize the throughput and lower cost, while this may directly affect the inventory level and increase the inventory level of downstream operations. Minimizing inventory level is one of the long-term management objective, which contradicts maximizing manufacturing throughput;
- Supply chain units traditionally operate independently. Research aimed at promoting integration and coordination is still at strategic level (Griffiths and Margetts 2000, Lendermann *et al.* 2001). As for coordination and integration at operational level, they are much more difficult to realize due to the complexity of communication, information sharing and shielding, as well as the need to search for a globally feasible or near optimal solution; and
- A supply chain especially an extended supply chain, which includes suppliers' and customers' supply chain networks, can be enormous as it may consist of a large number of supply chain units. A large-scale supply chain would drastically increase the complexity and adversely affect the effectiveness of the coordination as well.

Supply chain is stochastic and dynamic in the real business due to the uncertainties from demand, production capacity, lead-time, supply of materials and so on. Companies usually have to handle several conflicting objectives when making decision. The stochastic supply chain models have been extensively discussed in supply chain design and planning (Lin 2010, Sourirajan *et al.* 2007, Vidyarthi *et al.* 2009). Random variables and constraints with probability distributions have been used to reflect the stochastic nature of a supply chain. The

formulation of a stochastic model normally has much more variables and constraints than that of a deterministic model. It largely increases the difficulty in solving a stochastic model especially when an extended supply chain is in consideration.

This work attempts to address the above issues, i.e. scheduling and optimization of an extended supply chain. The prototype system is based on a deterministic supply chain model and is flexible and agile in response to dynamic events such as demand and production capacity variations. It involves the realization of a hierarchical model for supply chain coordination and optimization of all the supply chain units, such as suppliers, manufacturing plants, warehouses, distribution centres and customers. The proposed hierarchical model possesses the potential to support an extended supply chain environment, which takes into consideration suppliers' and customers' supply chain networks.

As mentioned in Chapter 2, many supply chain models lack the ability in providing a common supply-chain framework and standard terminology. In order to increase the flexibility and scalability, this work also explores the possibilities of using the Supply-Chain Operations Reference (SCOR) model described in Section 3.3, which provides a set of standard supply chain practices to create reusable, comprehensive procedures for a wide variety of supply chain activities, to model a supply chain. The representation can be further enhanced by a so-called Supply_Graph developed in this work (Khoo and Yin 2003). The Supply_Graph representation is comprehensive and flexible enough to facilitate the hierarchical model of a supply chain. It provides a detailed description of a supply chain network at the operational levels. It can handle complex supply chain units, customer order routings and transportation information to assist the individual functional modules in the proposed hierarchical model for supply chain coordination and optimization. As outlined in Section 1.4, the details of the SCOR model and the Supply_Graph are presented in Sections 3.3 and 4.2 respectively. Furthermore, an architecture of a novel evolutionary approach (Yin and Khoo 2007a) is proposed and described in Section 3.4. The approach is generic and can

be used to handle various supply chain optimization problems.

3.2 Proposed Framework of the Prototype System

Figure 3 - 2 A framework of the prototype SCASO system

In order to achieve a seamless integration of supply chain units for supply chain optimization, a distributed intelligent coordination and scheduling system that is able to support a materials

flow network in a global manufacturing environment is necessary. The supply chain coordination and schedule optimization system (SCASO) would help in resolving the conflicts among the requirements of supply chain units. A framework of the prototype SCASO system is shown in Figure 3-2. The prototype system comprises three main modules (Yin and Khoo 2007b). They are

- *Routing and Sequence Optimizer (RSO);*
- *Supply Chain Virtual Clustering (SCVC); and*
- *Supply Chain Order Scheduler (SCOS).*

The major functions of the three modules are as follows.

- In order to reflect the strategies at management level, the RSO module takes into account business strategies, customer requirements and the capacity of supply chain units to generate a preferred set of routing and work order process sequence that can be channelled to the SCVC module to form the so-call supply chain virtual clusters..
- The SCVC module is used to compartmentalize a complex supply chain optimization problem that can hardly be solved by conventional algorithms due to combinatory explosion into smaller and manageable clusters.
- The SCOS module is employed to work out the detailed plan and schedule for the entire supply chain through coordination among clusters.

Briefly, sales and marketing data such as customer orders, which are gathered by marketing personnel, and the detailed information about supply chain network and individual unit such as status, capacities and topology, are forwarded to the prototype system for processing. The prototype system (Figure 3-2) then invokes the RSO to generate intermediate data such as the preferred routings, transportation modes and work order plan based on the information stored in the supply chain network as well as management strategies such as constraints of customer service level, cycle time, cost, and so on. A hybrid heuristic based on GA and TS, and enhanced by a multiple populations search strategy (MPSS) is developed and used as the

MBEA enabled RSO optimization engine to tackle the routing and sequence optimization problem. Subsequently, it forwards the information obtained to the SCVC module. In order to efficiently derive the near global optimal solutions for the entire supply chain, the supply chain units, and transportation and related customer orders are virtually and dynamically organized into different supply chain unit-transportation-work order families based on the clustering technique, fuzzy c-means coupled with GA and TS as suggested in Section 2.5, and some performance measures. The clustering technique is further enhanced by the MPSS. A work order family can then be processed largely within a unit-transportation family with no or little disturbance to other supply chain families. This will compartmentalize a supply chain problem into sub-problems so as to reduce its search space and expedite flow planning and scheduling using the SCOS module. The SCOS module generates a near global optimal schedule for the entire supply chain. It minimizes the total cost and maximizes customer service level with the assistance of a scheduling engine for individual supply chain family, i.e. a virtual cluster, which takes into consideration such objective functions as machine utilization and cycle time from the SCVC module. It is supported by a distributed and intelligent agent-based mechanism to exchange information and promote negotiation and coordination within or among supply chain families. The detailed schedule is then examined and fine-tuned based on a compliance measure using the feedback information from the SCOS to the SCVC, and to the RSO. Here, the compliance measure, which is the degree (in percentage) in which the solution generated by a module complies with those derived by higher-level modules, is used to evaluate the performance of all the modules and fine-tune the detailed schedule of the SCOS. The e-business information flow network is used to provide the necessary order and the supply chain information for the prototype SCASO system. With such a framework, the long-term management objectives can be incorporated into the RSO for routing and sequence selection which guides the other two modules, namely SCVC and SCOS.

3.2.1 Assumptions of the Proposed Framework

Dell Inc. is best known for its success in direct selling computers to end users through the Internet. Its business model has been widely studied (Fan *et al.* 2007, Kraemer *et al.* 2000, Ross 2003). Comparing to the traditional personal computer makers such as IBM, Dell's business model has fewer stages in its supply chain while customer pulls products directly from Dell instead of a retailer (Figure 3-3). Customer orders received by Dell are processed and the product requirement and configuration are shared electronically with its suppliers. The suppliers are required to deliver immediately the components to Dell production facilities directly where the computers are assembled, tested, packed and shipped to the customers. Two significant and costly components, the retailer and the risks associated with carrying large inventories of components and final products have been eliminated (Figure 3-3).

a. Dell supply chain b. Traditional PC supply chain

Figure 3 - 3 Business models (adapted from Kraemer *et al.* 2000)

As mentioned in Section 3.1, the proposed SCASO system is able to handle both the Dell type of supply chains and traditional PC type of supply chains. As this work focuses on operational level supply chain planning and detail scheduling, the major information required and assumptions used are listed as follows.

- Order information includes product, order quantity and due date are provided. An order can be one that requested by a customer, i.e. built to order, or one that meets the demand

forecasted, i.e. built to stock;

- Production capacity of a manufacturing or assembly is known and can be calculated using equipment capacity if equipment capacity data are available;
- Transportation modes between supply chain units are given;
- Supplier capacity and delivery lead time or supplier's supply chain are available;
- Material cost / manufacturing cost / delivery cost / inventory cost / transportation cost etc. are predefined;
- Physical materials flow of a work order or a final product is given; and
- e-business information flow network that is integrated in the supply chain is able to provide and share the above information.

As mentioned in Section 3.1, this work concerns the operational level scheduling and optimization of an extended supply chain. As a result, the business model will not be considered in the prototype SCASO system. The prototype SCASO system gathers all the changes including the demand fluctuation, production capacity change and material delivery delay. It is able to respond to dynamic events and work out the new near-optimal plan and schedule for the entire supply chain rapidly.

Without loss of generality, a supply chain network that includes supplier, manufacturer, distribution centre, warehouse and customer (end user or client) will be used to illustrate the capability of the different modules developed in this work.

3.2.2 Routing and Sequence Optimizer (RSO)

A work order may have multiple routings, which denote the flow of materials, i.e. materials flow. Basically, materials flow indicates the sequence in which materials move from suppliers (raw materials) to manufacturers (intermediate product), and to customers (finished product) as shown in Figure 3-4. For each routing of a work order, it may use different materials and go through different manufacturing plants. For example, both DCs D1 and D2 are able to distribute the product of work order WO1 to meet the requirement from customer

order CO1. For this reason, a work order may have different cycle time, different cost and delivery date when choosing different supply chain units and routings.

Figure 3 - 4 Multiple routings of a typical supply chain

Since the capacity of each supply chain unit, such as a manufacturing plant, is limited, a near optimal routing and a work order process sequence are necessary for a mixture of work orders and products. Furthermore, the management level strategies can be incorporated into the prototype system. By selecting a proper combination of the routing and work order process sequence, better plans can be generated for the entire supply chain, which is effective in maintaining or even increasing the customer service level, reducing the inventory, transportation and production costs, and lowering the safety stock level.

As shown in Figure 3-2, a new hybrid heuristic, which combines the strengths of GA and TS for solving routing and sequence optimization problems, is reported. The RSO optimization engine is further enhanced by a so-called multiple populations search strategy (Yin and Khoo 2007b) that is able to facilitate the search process and help determining the GA parameters. In order to find better or at least suitable GA parameters that can improve the GA performance, an exact scheme theorem which extends the Goldberg's schema theorem is studied and the details of the exact schema theorem as well as the MBEA enhanced RSO are presented in Chapters 4 and 5 respectively.

3.2.3 Supply Chain Virtual Clustering (SCVC)

Typically, in optimizing a supply chain, customer orders, product flows, supply chain units, transportation, customer service level, and other resources and constraints are used as inputs to a simulation program, an optimization program or a heuristic rule based engine so as to derive a product plan or recommendations of inventories. As already mentioned, a complex extended supply chain optimization problem can hardly be solved by conventional algorithms due to combinatory explosion. An approach that is based on virtual clustering is proposed here to reduce the search space. The approach is likely to help deriving near optimal or at least good-enough solutions for a complex supply chain efficiently. The supply chain units, transportation and customer orders as shown in Figure 3-4 can be virtually and dynamically organized into different unit-transportation-work order families based on some performance measures (Section 6.3) before optimization. A work order family can then be processed largely within a unit-transportation family. Computational efficiency can be improved as a large-scale supply chain optimization problem has been compartmentalized into relatively small and manageable sub-problems.

Figure 3-2 shows the overall structure of the supply chain virtual clustering (SCVC) module and the main components. The details of the module are discussed in Chapter 6.

In the SCVC module, the input data comprises supply chain units, customer orders / work orders and transportation modes. Other constraints such as regional restrictions can also be included. Different combinations of performance measurements, including inter/intra cell transportation, loading balance and group efficiency, can be used to determine grouping patterns by the optimization engine. The similarity of each supply chain units-transportation-work order family can then be evaluated so as to guide the search to derive a near optimal or at least a good-enough solution. Heuristic procedures based on fuzzy c-means, GA and TS are used to determine the fuzzy cluster matrix.

More specifically, as mentioned in Section 2.5, the basic notions of Group Technology (GT) are adapted and enhanced by fuzzy c-means, GA and TS as the clustering technique for the SCVC module. A complex supply chain model can then be decomposed into smaller supply chain families. It is envisaged that the search space for the optimization of a complex supply chain can be reduced and as a result the efficiency of the search and optimization procedure to derive the near global optimal solution can be improved.

3.2.4 Supply Chain Order Scheduler (SCOS)

A supply chain may have various customer requirements and multiple end products with shared components and capacities. In order to fulfil customer order, materials and components from suppliers are transformed into final products by manufacturing and assembly plants, distributed to warehouses and distribution centres and finally delivered to customers. The optimal schedule of an individual supply chain unit may be in conflict with the requirements of other units and even deteriorate the overall performance of the entire supply chain. In order to handle such complex scheduling problems within a global manufacturing environment, a distributed intelligent coordination and scheduling mechanism is therefore necessary.

The SCOS module is an agent-based distributed supply chain order scheduling system (Figure 3-2). It consists of two subsystems, the Supply Chain Scheduling Master (SCSM) and the Supply Chain Scheduling Client (SCSC). The SCSM maintains all the domain knowledge and scheduling information in its database and communicates with all the SCSCs, which represent the supply chain clusters in the global manufacturing environment. The SCSM also provides a negotiation locale for the supply chain cluster agents to resolve any conflicts among local optimized schedules when they try to obtain the near optimal schedule for the entire supply chain. Basically, the SCOS module is supported by and built on top of the e-business information flow network, which enables the communication and coordination of geographically dispersed networks of resources. The SCSC works out the local near-optimal

schedule of a supply chain cluster by retrieving the necessary information from the SCSM. An existing genetic algorithm (GA)-enhanced dynamic scheduler by which the near-optimal local schedules are derived (Khoo *et al.* 2000, Yin 2000) is enhanced and embedded into the SCOS module.

Two types of agents have been deployed, namely the supply chain supervisory agent (SCSA) of the SCSM and the supply chain cluster agent (SCCA) of the SCSC. The SCOS module and the functional roles of the supervisory agent and supply chain cluster agents are presented in Chapter 7.

3.3 Modelling a Typical Supply Chain Using SCOR

As mentioned, the SCOR provides a general model for the representation of a supply chain as well as a set of standard supply chain practices for the creation of reusable and comprehensive procedures. This work attempts to highlight how the SCOR can be used and the Level 3 process elements are presented for manufacturing factory, distribution centre, warehouse, distribution centre, supplier, customer and transportation.

Figure 3 - 5 Functional units of a supply chain (Yin and Khoo 2007b)

Consider a supply chain as depicted in Figures 2-1 and 2-2. The customers, suppliers, warehouses, factories and other units in the supply chain are geographically dispersed in

different locations. The materials and information flows (Figure 3-5) connect different functional units of the supply chain as indicated by the lines, and coordinate the entire value chain, from customer order to production, storage, distribution and delivery. Monetary flow, though is an important part of the supply chain, is not within the scope of the work.

The supply chain modelled in this work covers three of the processes described in the SCOR model, namely Processes *Source*, *Make* and *Deliver*. Make-to-Stock (MTS), Make-to-Order (MTO) and Engineer-to-Order (ETO) associated with Processes *Source*, *Make* and *Deliver* are the main concerns here. The SCOR model can be easily extended to handle the supplier's supplier or the customer's customer within a global manufacturing environment. Process *Return* is not modelled here. Since this work attempts to address short-term operational supply chain optimization, Process *Plan*, which focuses mainly on the middle or long term production planning and control, is ignored. In addition, as the product design phase is not the focus of this work, for simplicity, the different processes of ETO and MTO are disregarded.

3.3.1 Modelling a Supply Chain

Figure 3-6 shows that the supplier provides the materials to be delivered to the various manufacturing sites. The information, which is extracted from upstream units such as transportation, management of inventory and incoming materials and product, is maintained by Process *Source*. Process *Make* schedules production activities, manages WIPs, equipment and facilities, and releases product to deliver. Process *Deliver* manages the order and inventory, and then transfers the product to downstream supply chain units, such as warehouse and distribution centre, and finally customers, through some means of transportation that exists between any two supply chain units. The customers here can be the end user of some suppliers of other manufacturing factories. All these functional units are not sequential events in a supply chain and may have multiple downstream units.

Figure 3 - 6 SCOR model of a typical supply chain

3.3.2 Modelling Supply Chain Units

Figure 3-7 illustrates the process elements of a manufacturing factory. Orders and materials from the upstream supply chain units, which may be suppliers, warehouses or another factory, are routed to the elements of Process *Source*. This includes ‘receive materials’ and ‘receive order information’. Materials are processed and transformed into products by the shop floors of factories, while some materials and in-process products may be temporarily stored in internal warehouse for further processing or for delivery. Internal transportation that concerns the movement of unfinished products within an establishment/factory has been included. In case the time required for internal transportation is too long, it needs to be taken into consideration when determining the detailed schedule. After the completion of all the processes, products are delivered to the next supply chain unit, such as warehouses or another factory.

Figure 3 - 7 Process elements of a manufacturing factory

Figure 3 - 8 Process elements of warehouse, distribution centre and transportation

Typically, the process elements of a warehouse and a distribution centre are shown in Figure 3-8. They receive products and order information from the upstream supply chain units, store and manage the products locally, and then distribute them to the downstream supply chain units. The warehouse places a MTS order if the inventory is below a safety stock. Figure 3-8 also shows the two process elements of transportation, which are ‘receive products’ and ‘deliver products’, either by airfreight, by train, by truck or by other means.

The modelling of suppliers and customers is relatively simple since it only concerns the modelling of ‘receive order information’ and ‘deliver materials by supplier’, and ‘place MTO order and receive product by customer’ as a part of the supply chain (Figure 3-9). The supplier and the customer may have their own supply chains. Other processes of the supplier and customer, which are similar to what have been described above, can be included when considering the supply chain of a virtual enterprise, a temporary alliance of enterprises

sharing capabilities, skills, core competencies and/or resources in order for a better business opportunity. For example, in order to provide an international service, a closely meshed network of subsidiaries and partners is formed in the MAN group, which is a large manufacturer of trucks and buses in Germany (Mehandjiev and Grefen 2010). ‘Other processes’ of a supply chain unit here means the processes of the customer’s supply chain that transform the materials/components into the final product and then deliver to its customers, or the processes of the supplier’s supply chain that transform the materials received from its suppliers into half finished product/components and then deliver to its customers.

Figure 3 - 9 Process elements of supplier and customer

3.4 MPSS Based Evolutionary Approach (MBEA)

As described in Section 3.2, in order to achieve better performance, the RSO and SCVC module utilize a hybrid evolutionary approach that combines GA and TS. The hybrid evolutionary approach is further enhanced by a multiple populations search strategy (MPSS). This MPSS based evolutionary approach (MBEA) developed in this work provides a generic optimization methodology that can be employed to handle different supply chain optimization applications. Figure 3-10 depicts the details of the proposed architecture of the MBEA.

The MBEA consists of five different layers that are able to fulfil different functions. They are common data storage layer, the MPSS layer, optimization algorithms layer, logic and computational layer, and application layer.

- Common data storage layer: This layer handles the data relevant to an optimization problem such as supply chain topology, customer order and supply chain unit capacity.
- MPSS layer: This layer contains the heuristic rules and procedures that are crucial to the application of the multiple populations search strategy. The MPSS is used to coordinate the GA, the TS and problem specific algorithms (PSAs), in which the TS is employed to optimize the parameters of GA and/or PSA, while GA is for optimization. With MPSS, the MBEA is able to search for the best solution of an optimization problem using the best possible parameters that enable the optimization algorithms to achieve better performance.
- Optimization algorithms layer: This layer contains the mathematical models, the basic routings and/or the heuristic rules of the optimization algorithms used in the MBEA. The standard GA and TS procedures have been incorporated into this layer. It can be customized for a particular optimization problem and PSA implemented.
- Logic and computational layer: This is the layer that specifies the details of each algorithm and carries out the necessary computations. It includes three parts.
 - (1) GA optimization logic: GA chromosome representation, GA operators such as crossover, mutation and selection and evaluation functions are specified when PSA is defined. It also identifies how the PSA optimization can be done by leveraging on the GA.
 - (2) GA parameters: It defines the heuristic rules that can be used to optimize the GA parameters. A so-call promise level that measures the performance of different GA parameters is also specified. The promise level serves as a guide for the MPSS and TS to find better GA parameters that might improve the performance of GAs.
 - (3) PSA parameters: Similar to GA parameters, it defines the heuristic rules to optimize the PSA parameters. The same concept of the promise level is employed. The promise level can guide the MPSS and TS to find better PSA parameters so as to optimize the physical optimization problem.
- Application layer: Physical optimization problems are defined in this layer. It includes the domain specific knowledge, the possible PSAs, etc. For instance, a machine-cell

formation problem can be defined in the application layer and it may be solved by a fuzzy c-means that is further specified as the PSA in optimization algorithms layer.

Figure 3 - 10 Architecture of a MPSS based evolutionary approach (MBEA)

3.5 Summary

This chapter describes a framework of the distributed intelligent system for multi-level supply chain coordination, optimization and order scheduling. The three main modules of the prototype SCASO system, namely Routing and Sequence Optimizer (RSO), Supply Chain Virtual Clustering (SCVC) and Supply Chain Order Scheduler (SCOS), have been presented. As mentioned, the Routing and Sequence Optimizer (RSO) is used to initialize the SCVC module with a good routing and work order process sequence combination while taking into consideration the capacity of each supply chain unit, the business strategy and the customer

requirements to maintain the required customer service level and competitiveness. The Supply Chain Virtual Clustering (SCVC) uses the output from the RSO module as the initial input and tries to compartmentalize a large-scale supply chain optimization problem that can hardly be solved by conventional algorithms into manageable sub-problems. The Supply Chain Order Scheduler (SCOS), which contains an agent-based distributed intelligent coordination and scheduling mechanism, integrates the scheduling with supply chain optimization. A reactive mechanism, which allows the fine-tuning of solutions based on the compliance measure of different modules, such as the measure between SCOS and SCVC or RSO, has also been proposed.

It is followed by a discussion on the details of a supply chain model, which covers three of the processes described in the SCOR model, namely Source, Make and Deliver. The SCOR provides a general model for the representation of a supply chain as well as a set of standard supply chain practices for the creation of reusable and comprehensive procedures. Using such a model, various supply chain units, such as manufacturing plants, warehouses, distribution centres, transportations, suppliers and customers can be adequately modelled and, subsequently, used to tackle short-term operational supply chain optimization problems

Finally, the architecture of a novel multiple populations search strategy based evolutionary approach (MBEA) is presented. The MBEA is basically a generic optimization methodology and can be applied to solve different supply chain optimization problems. It consists of five different layers that are used to fulfil different functionalities. They are common data storage layer, MPSS layer, optimization algorithms layer, logic and computational layer, and application layer. The MBEA will be deployed in the RSO and SCVC modules to handle relevant supply chain optimization problem.

Chapter 4 SUPPLY GRAPH AND EXACT SCHEMA THEOREM FOR AN ADAPTIVE GENETIC ALGORITHM

4.1 Introduction

As mentioned in Section 2.3, in order to analyze and coordinate the schedule of an entire supply chain, a comprehensive representation is fundamental and critical to facilitate the hierarchical modelling of a supply chain. Such a representation should be able to provide an enabling metrics, which is generic, flexible and sophisticated enough to incorporate important supply chain features at operational level. This chapter describes the basic notions of a so-call Supply_Graph developed in this work. Supply_Graph attempts to provide a comprehensive representation for supply chain modelling. It covers the modelling of supply chain units, customer order routings and transportation information. It lays the foundation for such modules as Routing and Sequence Optimizer (RSO) and Supply Chain Virtual Clustering (SCVC). This work also attempts to transform Supply_Graph into a so-called Supply_Matrix which is a part-machine-formation like matrix. In doing so, Group Technology (GT) can possibly be adapted to realize a virtual clustering module for supply chain applications.

On the other hand, Goldberg's schema theorem is fundamental to Genetic Algorithms (GAs). It can be used to estimate the survival and propagation of schemas from one generation to another. However, as mentioned in Section 2.5.3, the usefulness of the schema theorem has been criticised as it only provides the lower boundary instead of the exact expected number of schemas in the next generation. In this chapter, Goldberg's schema theorem is revisited and is extended to realize a so-called exact schema theorem, which takes into account the combined effects of reproduction, two-point crossover and mutation to enhance the

performance of GAs. The proposed exact schema theorem attempts to mathematically characterize the evolution of the population of a GA. This helps in making the prediction of the future behaviour of GAs possible. Further study on the exact schema theorem is conducted to examine the existence of the optimal crossover and mutation probabilities for each GA generation.

4.2 The Graph Representation of a Supply Chain

4.2.1 An Overview of Graph Theory in Supply Chain Management

Graph theory has been widely used in supply chain modelling to facilitate the design of supply chains and the analysis of supply chains at the strategic and tactical levels (Lakhal *et al.* 2001, Lin and Wang 2008, Luo *et al.* 2009, Pan *et al.* 2007, Perea *et al.* 2009). A typical supply chain network structure can be depicted generally as a directional and multi-layer graph (Luo *et al.* 2009).

Pan *et al.* 2007 proposed a local network based approach to reduce inventory and improve customer's service level in an n-tier complex distributed supply chain network. Lin and Wang (2008) discussed a directed graph for partner selection in a supply chain network based on such criteria as quality, cost and reputation of the partner. The partner selection problem had been transformed into an optimal path selection in graph theory. Perea *et al.* (2009) proposed a directed network to model a distribution problem (DiP in short in their paper), which included suppliers, intermediary centres and retailers. It was basically a network flow problem and was presented as a linear programming formulation to find an optimal distribution plan. Luo *et al.* (2009) proposed a multi-layer graph model to represent the materials flow and information flow as a base for supply chain analysis. The inter-connection and relationship of nodes in different layers were also depicted.

A supply chain network can also be modelled as Petri nets (Dotoli *et al.* 2009, Zhang *et al.* 2009). Basically, a Petri net is a directed bipartite graph that is widely used to describe some

distributed systems. It provides the mathematical definitions of modelling and execution for the process analysis. Dotoli *et al.* (2009) proposed a hybrid Petri net model to describe the materials, financial and information flows. The hybrid Petri net model was able to evaluate the performance of the system and help determine the design parameters. A coloured Petri net was developed by Zhang *et al.* (2009) to handle the coordination of product, process and logistics decision into supply chain configuration model.

However, the above mentioned models are not realistic when handling extended supply chain as the network problems formulated usually are huge which need plenty of computational efforts. They are system dependent and high degree of maintenance is expected in modelling complex systems. Furthermore, as mentioned in Section 2.3.1, the research efforts on the process flow from customer order to suppliers so as to support supply chain coordination and order scheduling along the entire supply chain at the operational level is lagging behind. It needs to take into consideration capacity limitations of individual supply chain unit, the processing time in each stage, the different transportation modes and various possible order routings. Thus, the graph representation proposed in this work has to be flexible enough to support the RSO module that analyses the supply chain units and work order routings. In addition, it also needs to be dynamic and can be easily modularized. It must be able to be converted into a part-machine-formation like matrix (Supply_Matrix), and virtually and dynamically organized a supply chain into smaller and manageable supply chain clusters by the SCVC module.

In view of the limitations described above, a novel graph representation that is flexible to model operational level supply chain characteristics and possesses the properties such as modularity and reusability is described in this chapter.

4.2.2 The Supply Chain Representation

A graph (Figure 4-1) is employed here to represent and analyze the business process of a

supply chain, from customer orders to suppliers. It is assumed that

- Supply chain units such as factories, DCs and warehouses can be represented by numbered nodes.
- Transportation method and the movement of materials or half-finished products can be represented by an arc between two nodes.
- Suppliers and customer orders/work orders can be represented by symbols, which are used to distinguish main supply chain units from other supplementary units such as customer order (CO) and work order (WO).
- The dotted line between customer order and work orders is used to indicate that a customer order can be separated into a few work orders.
- The multiple routings including transportation modes among supply chain units of a work order are predefined.
- The information is shared along the entire supply chain.

It is further assumed that

- Order information including product, order quantity and due date is provided. An order can be one that requested by a customer, i.e. built to order, or one that meets the demand forecasted, i.e. built to stock.
- The complete possible routings and materials flows of an order or a product are given. Such information has to be predefined even for the new products that routings have yet to finalize (to tentatively define the routing information).
- The flows of parts and components for sub-assembly and final assembly are known.
- Possible transportation modes between supply chain units are given.
- The uncertainties of the demand and capacity and the stochastic nature of supply chain are not considered.
- All the relevant information is shared across the supply chain units.

As highlighted in Section 4.1, the Supply_Graph (Khoo and Yin 2003) can be employed to model and depict the information about complex supply chain unit, customer order routing

and transportation in an efficient manner. It can also be used to facilitate computation of the functional modules, RSO and SCVC.

Accordingly, let the product structure of a work order, WO_i , of a customer order be represented by a Supply_Graph, G_i : $G_i = \{N_i, A_i\}$, with a set of nodes, N_i , and a set of arcs, A_i . The structures of m work orders of customer orders can be combined into a superimposed graph G with n nodes and k arcs where

$$G = G_1 \cup G_2 \cup G_3 \cup \dots \cup G_m \quad (4-1)$$

$$G_i = \{N_i, A_i\} \quad (4-2)$$

Figure 4 - 1 Graph representation of a supply chain

where:

G : Supply_Graph

G_i : Supply_Graph for work order i

N_i : Nodes involved in processing work order i

A_i : Arcs involved in processing work order i

m : Total number of work orders

n : Total number of nodes

k : Total number of arcs

$N = \{n_1, n_2, \dots, n_n\}$: Entire set of nodes

$A = \{a_1, a_2, \dots, a_k\}$: Entire set of arcs

In the RSO, the supply chain routing and sequence optimization problem can be translated into finding a routing combination of $G^* = G_1^* \cup G_2^* \cup G_3^* \cup \dots \cup G_m^*$, which optimizes some performance measures such as customer service level and the total cost.

As for the SCVC, Sets $N = \{n_1, n_2, \dots, n_n\}$ and $A = \{a_1, a_2, \dots, a_k\}$ are employed to denote n nodes (supply chain units) and k arcs (transportation methods) of a supply chain respectively, and Set $J = \{j_1, j_2, \dots, j_m\}$ is used to represent m work orders. Let Set $P = \{p_1, p_2, \dots, p_x\}$ be a partition of N , which contains x subsets (supply chain unit families) of N . Similarly, let $Q = \{q_1, q_2, \dots, q_x\}$ be a partition of A , which comprises x subsets (transportation method families) of A , and let $R = \{r_1, r_2, \dots, r_x\}$ be a partition of J , which has subsets (work order families) of J . Finally, let the collection of unit-transportation-work order families be

$$S = \{s_1, s_2, \dots, s_x\} \text{ such that } S \tilde{I} G$$

where

$$s_y = \{p_y, q_y, r_y\}, \text{ which is a unit-transportation-work order family.}$$

The purpose of performing virtual clustering, which is described in Chapter 6, is to determine the optimal unit-transportation-work order families, S^* ($S^* = \{p^*, q^*, r^*\}$), the number of families, x^* , and the logical description L^* that is described further in Section 4.2.2.2.

4.2.2.1 Graph Representation of a Supply Chain

Using the Supply_Graph (Khoo and Yin 2003), the product structure of WO_i can be represented as a matrix as follows.

$$M_i = \begin{matrix} & n_1 & n_2 & n_3 & \dots & n_n \\ \begin{bmatrix} y_{11} & y_{12} & y_{13} & \dots & y_{1n} \\ y_{21} & y_{22} & y_{23} & \dots & y_{2n} \\ \dots & & & & \\ y_{b1} & y_{b2} & y_{b3} & \dots & y_{bn} \end{bmatrix} & \left| \begin{array}{l} \text{Operation } 1 \\ \text{Operation } 2 \\ \dots \\ \text{Operation } b \end{array} \right. \end{matrix} \quad (4-3)$$

where

n The number of the nodes of the graph;

b The maximum number of operations WO_i needs to go through; and

$$y_{ef} = \begin{cases} 0 & \text{Node } n_f \text{ is not included in operation } e \\ 1 & \text{Node } n_f \text{ is included in operation } e \end{cases}$$

Each row in M_i represents one operation of WO_i while each element of a row represents the relevant node of Supply_Graph G . If it is “0”, the node is not included in the current operation. On the other hand, if it is “1”, the node is included in the current operation.

Basically, a Supply_Graph G is able to represent

- Multiple level assemblies with the aid of logical descriptions (Section 4.2.2.2). Figure 4-2a shows three continuous operations, namely Operations r , $r+1$, $r+2$, of a work order. Node 1 needs materials from Nodes 2 and 3, while Node 2 requires materials from Nodes 4, 5 and 6 subsequently. It indicates that the product has to go through sub-assembly at Node 2 and final assembly at Node 1. This can be represented as follows.

$$M_i = \begin{matrix} & n_1 & n_2 & n_3 & n_4 & n_5 & n_6 \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \end{bmatrix} & \left| \begin{array}{l} \text{Operation } r \\ \text{Operation } r+1 \\ \text{Operation } r+2 \end{array} \right. \text{ or } \begin{bmatrix} n_1 \\ n_2 \ n_3 \\ n_4 \ n_5 \ n_6 \end{bmatrix} \end{matrix} \quad (4-4)$$

The logical description between two nodes is presented in Section 4.2.2.2.

- Various modes of transportation. In Figure 4-2b, the arc between two nodes can be used to denote transportation with varied cost and delivery time attached.
- Work order. A customer order may consist of many products. It can be partitioned into different work orders, which can be handled by the supply chain upon receipt of the

customer order with the number of products requested and the batch sizes. The work orders are then processed and delivered by the supply chain. For example, Figure 4-1 shows that $CO1 = WO_1 \cup WO_2 \cup \dots$

Figure 4 - 2 Multiple level assembly and transportation between nodes

- Cross-boundary representation. Basically, Supply_Graph supports cross-boundary representation. It can be extended to handle the suppliers' and the customers' supply chain networks, and eventually, the entire business processes within an extended supply chain. For example, $G = G^1 \cup G^2 \cup \dots \cup G^x \cup \dots$, where G^x is the supply graph of a company of the extended supply chain and $x = 1, 2, \dots$, the number of the supply graphs. In so doing, collaboration among enterprises could be promoted.

4.2.2.2 Logical Relationship and the Extended Supply_Graph

With the Supply_Graph, possible routings of a product can be represented. However, as shown in Figure 4-2, it is difficult to represent such a relationship when Node 2 requires materials from either Node 4 or Nodes 5 and 6 by the graph alone. Thus, a logical description (L) needs to be introduced to realize an extended Supply_Graph so as to describe the relationship between two adjoining layers. Here, logical symbols, 'and gate', 'or gate', and 'exclusive or (xor)', are incorporated to enhance the Supply_Graph's ability in handling adjoining levels.

$$L = L_1 \cup L_2 \cup L_3 \cup \dots \cup L_n \quad (4-5)$$

where

n the number of the nodes of the graph;

Figure 4 - 3 Logical relationship among nodes

Figure 4-3 shows an example of the logical relationship between Nodes 5, 6, and 7 and Node 2. Here, assume Node 2 is a manufacturing plant requiring components from Nodes 5, 6, and 7, which may be the warehouses of half-finished products, the relationship can be depicted as follows.

$$L_2 = (n_7 \text{ and } n_6) \text{ or } (n_5 \text{ and } n_6) \quad (4-6)$$

Other than those described in Section 4.2.2.1, the extended graph representation, Supply_Graph with the aid of the logical descriptions, is able to represent:

- Multiple level assembly;
- Multiple split and merge of orders;
- Alternative locations or manufacturing sites for products and their components; and
- Other complex relationship, which can be depicted by the logical symbols between a node and the next-level of adjoining nodes.

With the introduction of the logical descriptions, the Supply_Graph for work order i can be extended as the follows.

$$G_i = \{N_i, A_i, L_i\} \quad (4-7)$$

where L_i is the logical description of work order i .

4.2.3 Routing Extraction and Supply_Matrix Converter

As mentioned in Section 4.1, Supply_Graph lays the foundation for functional modules, RSO and SCVC, to deal with supply chain problems. Basically, the RSO module is used to

generate the preferred routings, transportation modes and work order plan based on the information stored in the Supply_Graph which contains a complete list of routing and transportation information. The following procedures are used to extract the routing and transportation information from a Supply_Graph for a work order, i .

- (1) Retrieve the Supply_Graph $G_i = \{N_i, A_i, L_i\}$ of work order i .
- (2) Convert the Supply_Graph G_i to its relevant matrix M_i .
- (3) Examine all the elements in the matrix, M_i , and form the possible routings. Assign a number to identify each of the routings.
- (4) For each of the routings identified in Step 3, remove the unnecessary nodes by checking A_i and L_i .
- (5) A complete list of routings of work order i is then stored and forwarded to the RSO for further processing.

As for the SCVC module, the Supply_Graph can be converted into a so-called Supply_Matrix, which is a part-machine-formation like matrix that is frequently used in Group Technology. More specifically, a typical $n \times p$ Supply_Matrix, which represents n work orders and p supply chain units, is as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{p1} & x_{p2} & \dots & x_{pn} \end{bmatrix} = (x_{ij}) \quad (4-8)$$

where

p : total number of supply chain units

n : total number of work orders

$$x_{ij} = \begin{cases} 1, & \text{if supply chain unit } i \text{ process work order } j \\ 0, & \text{if supply chain unit } i \text{ doesn't process work order } j \end{cases}$$

$$i = 1, 2, \dots, p ; j = 1, 2, \dots, n$$

In a Supply_Matrix, supply chain units and work orders are mapped onto rows and columns

respectively. The mapping is done by a Supply_Matrix Converter that applies the following procedure.

- (1) Retrieve the Supply_Graph $G = G_1 \cup G_2 \cup G_3 \cup \dots \cup G_m$.
- (2) Convert the Supply_Graph G_j to its relevant matrix M_j .
- (3) Scan all the elements in the matrix, M_j . If supply chain unit i needs to process work order j , let element, x_{ij} , in the Supply_Matrix be '1'; otherwise, assign '0' to element x_{ij} .

4.2.4 An Example of the Supply_Graph

An example on a typical supply chain network is used here to illustrate the effectiveness of the proposed Supply_Graph.

Table 4 - 1 An example of supply chain network

Supply chain units	Symbol representation	Remarks
Customer Order	<i>CO1, CO2</i>	
Product	Products 1, 2, 3	Products requested in customer orders (<i>CO1</i> orders products 1, 2, and 3; <i>CO2</i> orders products 1 and 2)
Work Order	<i>WO1, WO2, WO3, WO4, WO5</i>	<i>WO1</i> and <i>WO2</i> request product 1; <i>WO3</i> and <i>WO4</i> request product 2; <i>WO5</i> requests product 3.
Manufacturing Plant	<i>P1, P2, P3, P4, P5</i>	<i>P1</i> and <i>P2</i> are assembly plants; <i>P3, P4</i> and <i>P5</i> provide components. They are regarded as Nodes 1, 2, 3, 4, 5 on the Supply_Graph respectively.
Warehouse	<i>W1, W2</i>	They are regarded as Nodes 6 and 7 on the Supply_Graph respectively.
Distribution Centre	<i>D1, D2</i>	They are regarded as Nodes 8 and 9 on the Supply_Graph respectively.
Supplier	<i>SU1, SU2</i>	They are regarded as Nodes 10 and 11 on the Supply_Graph respectively.

As shown in Table 4-1, the supply chain network consists of two customer orders (*CO1* and *CO2*) with three products, five manufacturing plants (*P1, P2, P3, P4* and *P5*), two warehouses (*W1* and *W2*), two distribution centres (*D1* and *D2*), and two supplier (*SU1* and *SU2*). The customer orders comprise five work orders based on the product and the priority of

customer orders. *CO1* consists of *WO1*, *WO3* and *WO5*, while *CO2* consists of *WO2* and *WO4*. *WO1* and *WO2* request Product 1, *WO3* and *WO4* request Product 2, and *WO5* requests Product 3. The different transportation means between two nodes are ignored here to simplify the graph representation and facilitate the discussion.

Figure 4 - 4 Graph representation of routings of work orders

Firstly, the business processes of the five work orders from two customer orders can be represented by Supply_Graphs shown in Figure 4-4. The numbered nodes have been replaced by the actual supply chain units in this example. For example, the routings to fulfil *WO1* and *WO2*, which request the same final product, Product 1, are shown in Figure 4-4a. Both distribution centres, *D1* and *D2*, can deliver the final product, Product 1, to partially fulfil the customer orders, *CO1* and *CO2*. *D1* receives the product only from the assembly plant, *P1*, while *D2* from either *P1* or *P2* or both of them. This kind of demand-supply relationship continues until the raw material suppliers are reached. Since the supply chain is not a very complicated one, all of the above descriptions can be easily represented using a

Supply_Graph (Figure 4-4a) and converted into the following matrix (Equation 4-9).

$$M_{WO1} = M_{WO2} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \text{ or } \begin{bmatrix} D1 & D2 \\ P1 & P2 \\ W1 \\ P3 & P4 & P5 \\ SU1 & SU2 \end{bmatrix} \quad (4-9)$$

Figure 4 - 5 Logical relationships

Secondly, the logical relationships between adjoining nodes are denoted by logical symbols. For instance, Assemble Plant $P2$ needs components directly from both Plants $P4$ and $P5$ before its product can be assembled. The logical symbol between them is an AND gate. Plant $P1$ requests components from Warehouse $W1$, which in turn receives components from Plants $P3$ and $P4$ or $P4$ and $P5$ (Figure 4-5). The logical relationships are given as follows.

$$L_{WO1} = L_{WO2} = D1 \text{ or } D2$$

$$L_{P2} = P4 \text{ and } P5$$

$$L_{W1} = (P3 \text{ and } P4) \text{ or } (P4 \text{ and } P5)$$

In doing so, the Supply_Graph is able to provide a detailed description of the supply chain network, the customer order routing and the logical relationships between adjoining nodes. Using the Supply_Matrix Converter and the procedure outlined in Section 4.2.3, the Supply_Matrix can be easily obtained (Equation 4-10).

$$\begin{array}{c}
 \begin{array}{cc}
 WO & 1 \quad 2 \quad 3 \quad 4 \quad 5 \\
 D1 & \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix} \\
 D2 & \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix} \\
 W1 & \begin{bmatrix} 1 & 1 & 0 & 0 & 1 \end{bmatrix} \\
 W2 & \begin{bmatrix} 0 & 0 & 1 & 1 & 0 \end{bmatrix} \\
 P1 & \begin{bmatrix} 1 & 1 & 0 & 0 & 1 \end{bmatrix} \\
 P2 & \begin{bmatrix} 1 & 1 & 1 & 1 & 0 \end{bmatrix} \\
 P3 & \begin{bmatrix} 1 & 1 & 1 & 1 & 0 \end{bmatrix} \\
 P4 & \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix} \\
 P5 & \begin{bmatrix} 1 & 1 & 0 & 0 & 1 \end{bmatrix} \\
 SU1 & \begin{bmatrix} 1 & 1 & 0 & 0 & 0 \end{bmatrix} \\
 SU2 & \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix}
 \end{array}
 \end{array}
 \quad (4-10)$$

4.3 An Exact Schema Theorem for Adaptive Genetic Algorithm

4.3.1 Overview

As mentioned in Section 2.5, genetic algorithms (GAs) can be enhanced by other techniques such as the tabu search to realize a hybrid approach. Such an approach is used extensively in this work to optimize the performance of a supply chain. It is a well known fact that as two important GA control parameters, crossover probability (p_c) and mutation probability (p_m) affect the performance of GAs drastically (Pham and Karaboga 2000). Essentially, a set of good GA parameters help in improving the ability of a GA to search for near global optimal solutions. As the mathematical foundation of GAs is weak and deterministic method for the selection of GA parameters does not exist, most of the GA applications require fine-tuning of GA parameters in order to achieve good results. Commonly used crossover operators such as one-point, two-point and uniform crossover operators have different impacts on the performance of GAs. Two-point and problem-specific crossover operators are frequently employed by many researchers, as they are believed to be able to outperform other types of crossover operators (Garrabos *et al.* 2008, Jiang *et al.* 2007, Lau *et al.* 2008, Rao and Lakshmi 2009, Ziver *et al.* 2004).

As previously mentioned, the proposed exact schema theorem, which is an extension of

Goldberg's schema theorem, takes into account the combined effects of reproduction, two-point crossover and mutation to enhance the performance of GAs. It is able to estimate the expected number of copies of schemas in the next GA generation and explore the possibility of deriving the optimal crossover and mutation probabilities.

4.3.2 The Schema Theorem

Based on the *Schema Theorem* or the Fundamental Theorem of Genetic Algorithms (Goldberg 1989), short, low-order, above-average schemas receive exponentially increasing trials in subsequent generations.

The combined effect of reproduction, one-point crossover and mutation as in a simple GA (Goldberg 1989) is given by Equation 4-11 as follows.

$$m(H, t+1) \geq m(H, t) \frac{f(H, t)}{\bar{f}(t)} (1 - p_c \frac{d(H)}{l-1}) (1 - p_m)^{o(H)} \quad (4-11)$$

where

$m(H, t)$	number of schema H at generation t
$f(H, t)$	average fitness value of the strings representing schema H at generation t
$\bar{f}(t)$	average fitness of entire population at generation t
p_c	crossover probability
$d(H)$	length of schema H
l	length of individual string
p_m	mutation probability
$o(H)$	order of schema H

As mentioned, in this work, Goldberg's schema theorem is further extended to handle a two-point crossover. For a combined effort of reproduction, two-point crossover and mutation, the schema theorem can be expanded. It is postulated that a schema H receives a number of copies in the next generation under reproduction, two-point crossover and mutation. The lower bound of the expected number of schemas H at time $t+1$ is given by Equation 4-12.

$$m(H, t+1) \geq m(H, t) \frac{f(H, t)}{\bar{f}(t)} [1 - p_c (\frac{d(H)}{l-1} + \frac{d(H)-1}{l-1})] (1 - p_m)^{o(H)} \quad (4-12)$$

Equation 4-12 can be easily derived as follows.

For normal reproduction while ignoring crossover and mutation, the expected number of schemas H at time $t+1$ can be expressed by Equation 4-13.

$$m(H, t+1) = m(H, t) \frac{f(H, t)}{\bar{f}(t)} \quad (4-13)$$

The expected number of schemas H at time $t+1$ when combining the effects of reproduction, two-point crossover and mutation is given by Equation 4-14.

$$m(H, t+1) = m(H, t) \frac{f(H, t)}{\bar{f}(t)} p(H)_t^c p(H)_t^m \quad (4-14)$$

where

$p(H)_t^c$ the survival probability of schema H under crossover at generation t

$p(H)_t^m$ the survival probability of schema H under mutation at generation t

Due to crossover operation, the schema may be destructed if any of the selected crossover points falls between the first and last positions of the schema H . As such, the survival probability using two-point crossover is as follows.

$$p(H)_t^c \geq 1 - p_c (\frac{d(H)}{l-1} + \frac{d(H)-1}{l-1}) \quad (4-15)$$

As for mutation,

$$p(H)_t^m = (1 - p_m)^{o(H)}$$

Thus, when combining the effects of reproduction, crossover and mutation,

$$m(H, t+1) \geq m(H, t) \frac{f(H, t)}{\bar{f}(t)} [1 - p_c (\frac{d(H)}{l-1} + \frac{d(H)-1}{l-1})] (1 - p_m)^{o(H)}$$

In order to achieve a better performance, p_c and p_m should not be fixed for all the

generations of a GA. Consider the lower-bound of $m(H, t+1)$ and ignore other “gains” and “losses” of schema from two-point crossover and mutation.

$$m(H, t+1) = m(H, t) \frac{f(H, t)}{\bar{f}(t)} [1 - p_c (\frac{d(H)}{l-1} + \frac{d(H)-1}{l-1})] (1 - p_m)^{o(H)} \quad (4-16)$$

Accordingly, if H is a good schema, p_c and p_m should be as close as possible to 0 in order to increase the survival probability of schema H . On the other hand, if H is a bad schema, p_c and p_m should be as large as possible in order to eliminate it. However, the values of p_c and p_m in GAs exhibit different or contradictory trends. For instance, p_c is normally set as high as possible so as to promote the probability that enables some child chromosomes to collect all the good schemas from their parents through interchanging the genes between the parent chromosomes; and p_m as low as possible in order not to degenerate the GA into a random search while still bringing in new schemas which prevents the GA from pre-mature convergence. Accordingly, an ideal set of optimal p_c and p_m may not be apparent. To handle this, an exact schema theorem is proposed and presented in Section 4.3.3.

4.3.3 The Proposed Exact Schema Theorem

Goldberg’s schema theorem focuses on the lower-bound of $m(H, t+1)$. An investigation into the exact schema theorem is described in this section.

The exact expected number of schemas H at time $t+1$ is given by Equation 4-17.

$$m(H, t+1) = \frac{f(H, t)}{\bar{f}(t)} \{m(H, t)(1 - p_m)^{o(H)} + p_c [ng^c(H, t) - m(H, t)](1 - p_m)^{o(H)} + np_m g^m(H, t)\} \quad (4-17)$$

where

n size of population

$g^c(H, t)$ the gain probability of schema H under crossover at generation t

$g^m(H, t)$ the gain probability of schema H under mutation at generation t

Crossover and mutation operations not only destroy the schema, but also create new chromosomes that contain the same and/or new schema (Whitley 2001). For example, if Chromosome '101010' is recombined (crossover operation) with Chromosome '010011' and the crossover points are at '2' and '4', two offspring, 110010, 001011, will be created. For offspring '110010', the crossover actually produces a new copy of schema, '11****', which does not exist in both parents. Similarly, if Chromosome '101010' is selected to undergo mutation and the mutation position is '3', it will create a new chromosome, '100010', which produces a new copy of schema, '**0***'. Such gains of new copies of schemas can be determined using Equation 4-17.

More specifically, Equation 4-17 can be easily derived as follows.

When considering selection and crossover operations, $m(H, t + 1)$ is given by Equation 4-18.

$$m(H, t + 1) = m(H, t) \frac{f(H, t)}{\bar{f}(t)} (1 - p_c) + n \frac{f(H, t)}{\bar{f}(t)} p_c g^c(H, t) \quad (4-18)$$

For any selected two positions (q_1 and q_2), i.e. two-point crossover, a chromosome can be split into three portions, the left portion from positions 1 to $q_1 - 1$, the middle portion from q_1 to q_2 , and the right portion from $q_2 + 1$ to l , where l is the length of chromosome. The gain, g_t^c , associated with crossover is

$$g^c(H, t) = \frac{2}{n(n-1)} \sum_{q_1=1}^n \sum_{q_2=q_1+1}^n [p^L(H, q_1, t) p^R(H, q_2, t) + p^M(H, q_1, q_2, t)] \quad (4-19)$$

where

q_1, q_2 the selected two positions for two-point crossover

q_3 the selected position for mutation

$p^L(H, q_1, t)$ the probability of the elements of schema H from positions 1 to $q_1 - 1$
at generation t

$p^R(H, q_2, t)$ the probability of the elements of schema H from positions $q_2 + 1$ to l

at generation t

$p^M(H, q_1, q_2, t)$ the probability of the elements of schema H from positions q_1 to q_2
at generation t

Mutation is then incorporated to obtain Equation 4-20.

$$m(H, t+1) = [m(H, t) \frac{f(H, t)}{\bar{f}(t)} (1 - p_c) + n \frac{f(H, t)}{\bar{f}(t)} p_c g^c(H, t)] (1 - p_m)^{o(H)} + n \frac{f(H, t)}{\bar{f}(t)} p_m g^m(H, t) \quad (4-20)$$

Assuming position q_3 has been selected to undergo mutation operation, the chromosome can similarly be split into three portions, the left portion from positions 1 to $q_3 - 1$, the middle portion at the mutation position q_3 , and the right portion from $q_3 + 1$ to l , where l is the length of the chromosome. The gain, g_t^m , which is associated with the mutation, is given by Equation 4-21.

$$g^m(H, t) = \frac{1}{n} \sum_{q_3=1}^n [p^L(H, q_3, t) p^R(H, q_3, t) p^M(H, q_3, t)] \quad (4-21)$$

where

$p^L(H, q_3, t)$ the probability of the elements of schema H from positions 1 to $q_3 - 1$
at generation t

$p^R(H, q_3, t)$ the probability of the elements of schema H from positions $q_3 + 1$ to l
at generation t

$p^M(H, q_3, t)$ the probability of the element mutated to be of schema at position
 q_3 at generation t

Thus, after rearranging Equation 4-20, the exact expected number of schemas H at time $t+1$ is given as follows.

$$m(H, t+1) = \frac{f(H, t)}{\bar{f}(t)} \{m(H, t) (1 - p_m)^{o(H)} + p_c [n g^c(H, t) - m(H, t)] (1 - p_m)^{o(H)} + n p_m g^m(H, t)\} \quad (4-22)$$

Equation 4-22 accurately describes the combined efforts of reproduction, two-point crossover

and mutation. It provides an avenue that is based on the population and average fitness values of the entire population and the individual schema in generation t to estimate the exact expected number of each schema in generation $t+1$, instead of giving the lower boundary only by using the schema theorem. This also makes the prediction of the future behaviour of a GA possible.

4.3.4 Analysis on Crossover and Mutation Probabilities

Most GA-based applications require fine-tuning of GA parameters in order to achieve better results. In this section, the existence of the optimal p_c and p_m will also be examined by analysing the extreme value obtained from the exact schema equation, Equation 4-17 as follows.

If p_m is sufficiently small, the exact schema equation (Equation 4-17) can be simplified as follows.

$$m(H, t+1) = \frac{f(H, t)}{\bar{f}(t)} \{m(H, t)(1 - p_m o(H)) + p_c [ng^c(H, t) - m(H, t)][1 - p_m o(H)] + np_m g^m(H, t)\} \quad (4-23)$$

By replacing some parts of Equation 4-23 that are not relevant to p_c and p_m , it can be further simplified as follows.

$$m(H, t+1) = A(H, t)[m(H, t)(1 - p_m o(H)) + p_c B(H, t)(1 - p_m o(H) + p_m C(H, t))] \quad (4-24)$$

where

$$A(H, t) = \frac{f(H, t)}{\bar{f}(t)}$$

$$B(H, t) = ng^c(H, t) - m(H, t)$$

$$C(H, t) = ng^m(H, t)$$

Thus, in Generation t of a GA population, $m(H, t)$, $A(H, t)$, $B(H, t)$ and $o(H)$ can be readily determined. The exact schema theorem possesses the following properties.

Property 1

$A(H, t) = \frac{f(H, t)}{f(t)}$ is always greater than zero, i.e. $A(H, t) > 0$, since the fitness and average

fitness values are always greater than zero.

Property 2

$o(H)$, the order of schema H , is greater than zero.

Property 3

$B(H, t) = ng^c(H, t) - m(H, t)$ and $B(H, t)$, in most cases, is non-zero as the chance of having $ng^c(H, t) = m(H, t)$ is very rare considering $g^c(H, t)$ a real number, which is given by Equation 4-19, and $m(H, t)$ an integer.

Based on the theory of extrema of functions of several variables (Smith and Minton 2006), the first and second partial derivatives can be used to determine the extrema of p_c and p_m .

The first partial derivatives $f_{p_c}(p_c, p_m)$ and $f_{p_m}(p_c, p_m)$ are given as follows.

$$\begin{aligned} f_{p_c}(p_c, p_m) &= A(H, t)[B(H, t)(1 - p_m o(H))] \\ f_{p_m}(p_c, p_m) &= A(H, t)[-m(H, t)o(H) - p_c B(H, t)o(H) + C(H, t)] \end{aligned}$$

The second partial derivatives, $f_{p_m p_m}(p_c, p_m)$, $f_{p_c p_c}(p_c, p_m)$ and $f_{p_c p_m}(p_c, p_m)$ are expressed as follows.

$$\begin{aligned} f_{p_c p_c}(p_c, p_m) &= 0 \\ f_{p_m p_m}(p_c, p_m) &= 0 \\ f_{p_c p_m}(p_c, p_m) &= -A(H, t)B(H, t)o(H) \end{aligned}$$

Thus,

$$f_{p_c p_c}(p_c, p_m)f_{p_m p_m}(p_c, p_m) - f_{p_c p_m}(p_c, p_m)^2 = -[A(H, t)B(H, t)o(H)]^2 \quad (4-25)$$

From Equation 4-25,

Deduction 1

As $A(H, t)$ and $o(H)$ are both greater than zero, the value of $B(H, t)$ will determine whether the $f_{p_c p_c}(p_c, p_m)f_{p_m p_m}(p_c, p_m) - f_{p_c p_m}(p_c, p_m)^2$ in Equation 4-25 is greater than zero or equal to zero.

Deduction 2

If $B(H, t) \neq 0$, then $f_{p_c p_c}(p_c, p_m)f_{p_m p_m}(p_c, p_m) - f_{p_c p_m}(p_c, p_m)^2 < 0$. This indicates that the optimal or extrema p_c and p_m do not exist.

Deduction 3

As mentioned in Property 3, $B(H, t)$, in most cases, is non-zero as the chance of having $ng^c(H, t) = m(H, t)$ is very rare. Having $f_{p_c p_c}(p_c, p_m)f_{p_m p_m}(p_c, p_m) - f_{p_c p_m}(p_c, p_m)^2 = 0$ is therefore extremely difficult to achieve.

From Deductions 1 - 3, it can be concluded that the optimal p_c and p_m do not exist in most cases. Hence, a compromised pair of p_c and p_m in each GA generation needs to be determined in order to ensure near optimal performance. Such a property is illustrated in Section 4.3.5.

4.3.5 Applications of the Exact Schema Theorem

The mathematical deductions outlined in Sections 4.3.3 and 4.3.4 has shed some lights on how the behaviour of a GA can be predicted and how the performance of GA parameters, namely the probabilities of crossover p_c and mutation p_m , can be determined using the proposed exact schema theorem. More importantly, the optimal p_c and p_m have been shown to be non-existence in most cases. In this section, an attempt is made to examine the existence of a compromised pair of p_c and p_m that is suggested by the exact schema theorem and is able to guarantee better GA performance. Accordingly, the author employed the MBEA described in Section 3.4 to look for better and suitable compromised pair of p_c and p_m for GA runs. The MBEA (Yin and Khoo 2007a) was initially developed for work order routing

selection and sequence optimization, i.e. the RSO module, of a supply chain. A detailed discussion of the MBEA for RSO is summarized in the next chapter, Chapter 5.

MBEA enabled fuzzy c-means is developed to solve the supply chain clustering problem. Basically, the evolutionary approach combines the strengths of genetic algorithms (GA) and the tabu search (TS) to realize a hybrid technique that is able to identify the compromised p_c and p_m and search for the best solutions with the aid of the MPSS. From the study, it will be shown that a compromised pair of GA parameters, i.e. p_c and p_m , can be found, and as a result, better GA performance and the near optimal supply chain group can be obtained. As mentioned in Sections 2.3 and 2.5 as well as in Chapter 3, the basic notions of Group Technology (GT) can possibly be adapted to realize a virtual clustering module for supply chain, i.e. the SCVC module in Chapter 6. By extrapolation, it is envisaged that the MBEA enabled fuzzy c-means can be extended to deal with virtual clustering of a supply chain, which is represented in the form of a Supply_Matrix using the Supply_Matrix Converter developed in this work.

4.3.5.1 Fuzzy C-Means Clustering Algorithm

Fuzzy models are good for measuring and expressing the fuzziness in a system. The element that is considered in fuzzy c-means is given a degree of membership that ranges from ‘0’ (not an element of the set) to ‘1’ (a member of the set). The underlining principle of fuzzy c-means clustering is summarized as follows (Lowen 1996, Josien and Liao 2000).

For a sample set X with n samples

$$X = \{x_1, x_2, \dots, x_n\} \quad (4-26)$$

Each x_j has p attributes

$$x_j = (x_{1j}, x_{2j}, \dots, x_{pj}) \quad (4-27)$$

Thus, X can be represented as a $p \times n$ matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{p1} & x_{p2} & \dots & x_{pn} \end{bmatrix} = (x_{ij}) \quad (4-28)$$

where

x_{ij} : the value of the attribute l of sample j , $l = 1, 2, \dots, p$; $j = 1, 2, \dots, n$

Because of the unit of measurement of different attributes may vary, normalization is performed before clustering. After normalization, a new matrix R is formed from X .

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \dots & \dots & \dots & \dots \\ r_{p1} & r_{p2} & \dots & r_{pn} \end{bmatrix} = (r_{ij}) \quad (4-29)$$

where

r_{ij} : the value of the attribute l of sample j after normalization, range from $[0,1]$ $l = 1, 2, \dots, p$; $j = 1, 2, \dots, n$

If n samples with p attributes are grouped into c clusters, the fuzzy cluster matrix is given as follows.

$$U = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{c1} & u_{c2} & \dots & u_{cn} \end{bmatrix} = (u_{ij}) \quad (4-30)$$

where

u_{ij} : degree of membership of sample j to cluster i

subject to:

$$\begin{aligned} 0 \leq u_{ij} \leq 1, \quad i = 1, 2, \dots, c; j = 1, 2, \dots, n \\ \sum_{i=1}^c u_{ij} = 1, \quad j = 1, 2, \dots, n \\ 0 < \sum_{j=1}^n u_{ij} \leq n, \quad i = 1, 2, \dots, c \end{aligned} \quad (4-31)$$

Assume that the cluster centres of c clusters are known, which is a $p \times c$ matrix V

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1c} \\ v_{21} & v_{22} & \dots & v_{2c} \\ \dots & \dots & \dots & \dots \\ v_{p1} & v_{p2} & \dots & v_{pc} \end{bmatrix} = (v_{li}) \quad (4-32)$$

where

v_{li} : eigenvalue of attribute l to cluster i , $0 \leq v_{li} \leq 1$

$$v_{li} \text{ can also be given as } v_{li} = \frac{\sum_{j=1}^n (u_{ij})^m x_{lj}}{\sum_{j=1}^n (u_{ij})^m}$$

The vector of p attributes of sample j is

$$r_j = (r_{1j}, r_{2j}, \dots, r_{pj})^T \quad (4-33)$$

The eigenvalue vector of p attributes of cluster i in cluster centre is then given by

$$v_i = (v_{1i}, v_{2i}, \dots, v_{pi})^T \quad (4-34)$$

Assuming the weightage vector of attributes is given by

$$w = (w_1, w_2, \dots, w_p)^T \quad (4-35)$$

The distance between sample j and cluster i can be calculated using the weighted Euclidean as follows.

$$d_{ij} = \sqrt{\sum_{l=1}^p w_l (r_{lj} - v_{li})^2} \quad (4-36)$$

In order to obtain the optimal fuzzy cluster matrix, a commonly used objective function is conceived which is the membership weighted within cluster error and is given as follows.

$$\min\{J_m(U, V) = \sum_{j=1}^n \sum_{i=1}^c (u_{ij})^m (d_{ij})^2\} \quad (4-37)$$

where $m \in [1, \infty]$ is the weighting exponent on each fuzzy membership. The larger the m is, the fuzzier the partition will be. Normally, the value of m is between 1.25 and 3.

4.3.5.2 Problem Definition

A typical $n \times p$ Supply_Matrix, which represents n work orders and p supply chain units, can be expressed using Equation 4-38 as follows.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{p1} & x_{p2} & \dots & x_{pn} \end{bmatrix} = (x_{lj}) \quad (4-38)$$

where

p : Total number of attributes / total number of supply chain units.

n : Total number of data points / total number of work orders.

$x_j = (x_{1j}, x_{2j}, \dots, x_{pj})$ is the j^{th} data point (work order) with attributes (supply chain units).

$$x_{lj} = \begin{cases} 1, & \text{if supply chain unit } l \text{ process work order } j \\ 0, & \text{if supply chain unit } l \text{ doesn't process work order } j \end{cases}$$

$$l = 1, 2, \dots, p; j = 1, 2, \dots, n$$

In fuzzy clustering, classification results can be expressed as a fuzzy cluster matrix as shown in Equation 4-30.

A fuzzy c-means algorithm is used in this work to search for the best U . Since the number of possible U matrices that satisfy the constraints is infinite, an objective function has to be defined to optimize the solution. The sum of the square error function which measures the dissimilarity between the data points and their cluster centre by the Euclidean distance is often used (Li *et al.* 2002, Pang *et al.* 2007). It can be defined using Equation 4-37.

$$\min\{J_m(U, V) = \sum_{j=1}^n \sum_{i=1}^c (u_{ij})^m (d_{ij})^2\}$$

where

$$(d_{ij})^2 = |x_j - v_i|^2 = \sum_{l=1}^p (x_{jl} - v_{il})^2 \text{ is the Euclidean distance.}$$

$v_i = (v_{i1}, v_{i2}, \dots, v_{ip})$ is the i^{th} cluster centre.

$$v_{li} = \frac{\sum_{j=1}^n (u_{ij})^m x_{ij}}{\sum_{j=1}^n (u_{ij})^m} \quad (4-39)$$

In optimizing the Supply_Matrix, normalization as mentioned in 4.3.5.1 is not necessary as the measurement units of different attributes are the same. So x_j in this situation is the same as r_j .

4.3.5.3 MBEA Enabled Fuzzy C-Means for Solving Supply_Matrix

Figure 4 - 6 Flow chart of the proposed MBEA enabled FCM algorithm

As shown in Figure 4-6, TS can be integrated with a GA to realize an enhanced multiple populations search strategy (MPSS) and the MBEA that is able to help determine the

compromised pair of GA parameters for the generation of next generation of chromosomes and facilitate the search for near optimal solutions. Basically, the aforementioned routing selection and sequence optimization problem is a minimization problem which aims at minimizing $J_m(U, V)$.

Figure 4 - 7 Searching and updating of GA parameters

More specifically, in each GA run, multiple populations with different GA parameters are maintained. These populations are then treated as ‘individuals’ in the tabu search and are concurrently reproduced by GAs. At the end of each iteration, the promise level for each parameter set, which is given by the fitness value attained by the objective function (Equation 4-41) during the tabu search, can be computed by Equations 4-44 and 4-45. The best parameter set in terms of promise level is then selected. From the tabu search point of view,

the GA run is used to evaluate the objective function, i.e. the promise level, of a parameter set, while the number of populations of a GA is the number of individuals maintained in the tabu search. For clarity, for every five generations of GA runs, the promise level of each parameter set is evaluated and used as the value attained by the objective function. A neighbourhood parameter set is created and employed in subsequent GA runs. The procedures for searching and updating of GA parameters and for generating neighbourhood parameter set are depicted in Figures 4-7 and 4-8, respectively.

As shown in Figure 4-8, in the neighbourhood creation, the length of steps taken by p_c and p_m , namely s_c and s_m , are determined by the maximum $(s_c^{\max}, s_m^{\max})$ and minimal steps $(s_c^{\min}, s_m^{\min})$ of the p_c and p_m respectively.

4.3.5.4 Chromosome Representation

In this work, a $c \times n$ matrix, U , which represents a fuzzy c -partition, can be treated as a chromosome in GA terminology. Each gene of a chromosome is denoted by an element of the matrix, U , i.e. ' u_{ij} ', which is the degree of membership.

$$U = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{c1} & u_{c2} & \dots & u_{cn} \end{bmatrix} = u_{ij} \quad (4-40)$$

For an ' n -work order c -cluster centre' problem, a chromosome contains $c \times n$ genes. For example, for a 2×3 problem, chromosome '0.5, 0.3, 0.2, 0.5, 0.7, 0.8' can be used to represent the matrix $U_{2 \times 3}$.

$$U_{2 \times 3} = [u_{ij}]_{2 \times 3} = \begin{bmatrix} x_1 & x_2 & x_3 \\ 0.5 & 0.3 & 0.2 \\ 0.5 & 0.7 & 0.8 \end{bmatrix} \begin{matrix} \\ c1 \\ c2 \end{matrix}$$

This implies that work orders x_1 , x_2 and x_3 can be grouped into two clusters, $c1$ and $c2$. The

numerical values in the matrix $U_{2 \times 3}$ represent the degree of the membership of the work order to the corresponding cluster centre.

Figure 4 - 8 Neighbourhood creation for tabu search

The initial chromosome of GA population is generated randomly through the following steps:

- (1) Generate $c \times n$ random numbers $y_{11}, y_{12}, \dots, y_{cn}$, $y_{ij} \in [1, 1000]$, $i = 1, 2, \dots, c$; $j = 1, 2, \dots, n$.
- (2) Use $u_{ij} = \frac{y_{ij}}{\sum_{i=1}^c y_{ij}}$ to form a chromosome.
- (3) Repeat steps (1) and (2) to generate the entire GA population.

4.3.5.5 Fitness Evaluation and Promise Level Calculation

The fitness or relative fitness of chromosomes needs to be evaluated in order to select suitable chromosome pairs for genetic operations. The evaluation process normally comprises fitness calculation, scaling and ranking. As mentioned in Section 4.3.5.2, the sum of square error $J_m(U, V)$, which is the measurement of the fuzzy cluster matrix, is used to calculate the fitness value. Basically, $J_m(U, V)$ is used to compute the sum of square error of the sample data in relation to the cluster centres. It will be minimal when the fuzzy cluster matrix is optimum. The fitness function is given by Equation 4-41 as follows.

$$J_m(U, V) = \sum_{j=1}^n \sum_{i=1}^c (u_{ij})^m (d_{ij})^2 \quad (4-41)$$

where

$$(d_{ij})^2 = |x_j - v_i|^2 = \sum_{l=1}^p (x_{jl} - v_{il})^2 \quad (4-42)$$

Here, d_{ij} is the distance between sample j and cluster i and can be calculated using the Euclidean distance.

A minimization problem needs to be transformed into a maximization problem in order to apply the GA. The transformation can be easily realized using Equation 4-43 (Goldberg 1989).

$$f(x) = \begin{cases} C_{\max} - J_m(U, V) & \text{if } C_{\max} - J_m(U, V) > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4-43)$$

Here, C_{max} can be assigned a value initially or assigned the largest value of $J_m(U, V)$ in the current GA population.

The promise level of a parameter set for a population can be derived using Equation 4-44.

$$p_{km} = w_{best} f_{km}^{best} + w_{avg} f_{km}^{avg} \quad (4-44)$$

$$w_{best} + w_{avg} = 1 \quad (4-45)$$

where

f_{km}^{best} : Fitness value of the best chromosome of m^{th} population of k^{th} generation.

f_{km}^{avg} : Average fitness value of chromosomes of m^{th} population of k^{th} generation.

p_{km} : Current promise level of GA parameters in of m^{th} population of k^{th} generation.

w_{best} : Weight of the relative fitness of the best chromosome in terms of the fitness value of a population. It is fixed at 0.8 in this research.

w_{avg} : Weight of the average relative fitness of a population. It is fixed at 0.2 in this study.

4.3.5.6 GA Operators

Much of the power of GAs derives from the recombination of genes such as crossover, mutation and inversion operations, which helps in exploring the virgin search space. In this work, three genetic operators, crossover, mutation and selection, are used to generate offspring chromosomes.

Crossover operator

Traditional crossover operation might create illegal offspring that cannot satisfy the constraint of the fuzzy cluster matrix U described in Section 4.3.5.1. This work proposed three types of crossover operations, namely partial exchange, overall exchange and neighbourhood search. These operations ensure the legality of the offspring while each of them serves different purpose. Specifically, partial exchange keeps the traits of parents and only swaps the selected columns in the fuzzy cluster matrix; the overall exchange replaces the

entire parents by applying the ratios c_1 and c_2 using Equations 4-46 and 4-47; the neighbourhood search, as its name implies, attempts to explore the neighbourhood of each ' u_{ij} '. For each generation, GA randomly selects one of them for crossover operation. The details of the three crossover operations are described as follows.

Let p_c be the crossover probability. U_1 and U_2 are two parents selected to undergo crossover operation and U_1' and U_2' are the offspring generated by the crossover operation.

- Partial exchange (Figure 4-9)

- (1) Select a pair of chromosomes randomly based on the crossover probability, p_c ;
- (2) Choose two integers p_1 and p_2 between 1 and n randomly; and
- (3) Exchange the selected columns between p_1 and p_2 in the two parents to generate the two offspring.

Figure 4 - 9 Partial exchange

- Overall exchange (Figure 4-10)

- (1) Select a pair of chromosomes randomly based on the crossover probability, p_c ;
- (2) Choose c_1^1, c_1^2, c_2^1 and c_2^2 between 0 and 1 randomly, where $c_1^1 + c_1^2 = 1$ and $c_2^1 + c_2^2 = 1$; and
- (3) Equations 4-46 and 4-47 will then be used to generate the two offspring.

$$U_1' = c_1^1 \times U_1 + c_1^2 \times U_2 \quad (4-46)$$

$$U_2' = c_2^1 \times U_1 + c_2^2 \times U_2 \quad (4-47)$$

$$\begin{aligned}
 U_1 &= \begin{bmatrix} u1_{11} & \dots & u1_{1p_1} & \dots & u1_{1p_2} & \dots & u1_{1n} \\ u1_{21} & \dots & u1_{2p_1} & \dots & u1_{2p_2} & \dots & u1_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u1_{c1} & \dots & u1_{cp_1} & \dots & u1_{cp_2} & \dots & u1_{cn} \end{bmatrix} & U_2 = \begin{bmatrix} u2_{11} & \dots & u2_{1p_1} & \dots & u2_{1p_2} & \dots & u2_{1n} \\ u2_{21} & \dots & u2_{2p_1} & \dots & u2_{2p_2} & \dots & u2_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u2_{c1} & \dots & u2_{cp_1} & \dots & u2_{cp_2} & \dots & u2_{cn} \end{bmatrix} \\
 &\downarrow \\
 U'_1 &= \begin{bmatrix} c_1^1 u1_{11} + c_1^2 u2_{11} & \dots & c_1^1 u1_{1p_1} + c_1^2 u2_{1p_1} & \dots & c_1^1 u1_{1p_2} + c_1^2 u2_{1p_2} & \dots & c_1^1 u1_{1n} + c_1^2 u2_{1n} \\ c_1^1 u1_{21} + c_1^2 u2_{21} & \dots & c_1^1 u1_{2p_1} + c_1^2 u2_{2p_1} & \dots & c_1^1 u1_{2p_2} + c_1^2 u2_{2p_2} & \dots & c_1^1 u1_{2n} + c_1^2 u2_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ c_1^1 u1_{c1} + c_1^2 u2_{c1} & \dots & c_1^1 u1_{cp_1} + c_1^2 u2_{cp_1} & \dots & c_1^1 u1_{cp_2} + c_1^2 u2_{cp_2} & \dots & c_1^1 u1_{cn} + c_1^2 u2_{cn} \end{bmatrix} \\
 U'_2 &= \begin{bmatrix} c_2^1 u1_{11} + c_2^2 u2_{11} & \dots & c_2^1 u1_{1p_1} + c_2^2 u2_{1p_1} & \dots & c_2^1 u1_{1p_2} + c_2^2 u2_{1p_2} & \dots & c_2^1 u1_{1n} + c_2^2 u2_{1n} \\ c_2^1 u1_{21} + c_2^2 u2_{21} & \dots & c_2^1 u1_{2p_1} + c_2^2 u2_{2p_1} & \dots & c_2^1 u1_{2p_2} + c_2^2 u2_{2p_2} & \dots & c_2^1 u1_{2n} + c_2^2 u2_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ c_2^1 u1_{c1} + c_2^2 u2_{c1} & \dots & c_2^1 u1_{cp_1} + c_2^2 u2_{cp_1} & \dots & c_2^1 u1_{cp_2} + c_2^2 u2_{cp_2} & \dots & c_2^1 u1_{cn} + c_2^2 u2_{cn} \end{bmatrix}
 \end{aligned}$$

Figure 4 - 10 Overall exchange

- Neighbourhood search (Figure 4-11)

$$\begin{aligned}
 U_1 &= \begin{bmatrix} u1_{11} & \dots & u1_{1p_1} & \dots & u1_{1p_2} & \dots & u1_{1n} \\ u1_{21} & \dots & u1_{2p_1} & \dots & u1_{2p_2} & \dots & u1_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u1_{c1} & \dots & u1_{cp_1} & \dots & u1_{cp_2} & \dots & u1_{cn} \end{bmatrix} & U_2 = \begin{bmatrix} u2_{11} & \dots & u2_{1p_1} & \dots & u2_{1p_2} & \dots & u2_{1n} \\ u2_{21} & \dots & u2_{2p_1} & \dots & u2_{2p_2} & \dots & u2_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u2_{c1} & \dots & u2_{cp_1} & \dots & u2_{cp_2} & \dots & u2_{cn} \end{bmatrix} \\
 &\downarrow \\
 U'_1 &= \begin{bmatrix} u1_{11} + s_c & \dots & u1_{1p_1} + s_c & \dots & u1_{1p_2} + s_c & \dots & u1_{1n} + s_c \\ u1_{21} - s_c & \dots & u1_{2p_1} - s_c & \dots & u1_{2p_2} - s_c & \dots & u1_{2n} - s_c \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u1_{c1} + s_c & \dots & u1_{cp_1} + s_c & \dots & u1_{cp_2} + s_c & \dots & u1_{cn} + s_c \end{bmatrix} \\
 U'_2 &= \begin{bmatrix} u2_{11} + s_c & \dots & u2_{1p_1} + s_c & \dots & u2_{1p_2} + s_c & \dots & u2_{1n} + s_c \\ u2_{21} - s_c & \dots & u2_{2p_1} - s_c & \dots & u2_{2p_2} - s_c & \dots & u2_{2n} - s_c \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ u2_{c1} + s_c & \dots & u2_{cp_1} + s_c & \dots & u2_{cp_2} + s_c & \dots & u2_{cn} + s_c \end{bmatrix}
 \end{aligned}$$

Note: assuming that the number of cluster centre, c , is an odd number

Figure 4 - 11 Neighbourhood search

- (1) Select one chromosome randomly based on the crossover probability, p_c ;
- (2) For each of the gene u_{ij} which is a real number, apply $u'_{ij} = u_{ij} + s_c$ if i is an odd

number and $u'_{ij} = u_{ij} - s_c$ if i is an even number, where s_c is the interval defined by the user;

(3) $U'_1 = [u'_{ij}]$; and

(4) Adjust the last row of U'_1 and make sure that the constraints for the fuzzy cluster matrix can be satisfied.

This neighbourhood search does not look like a normal crossover operator which commonly involves two parent chromosomes that exchange building blocks. However, as the neighbourhood search changes the value of every single gene, it incurs considerable variations of schemas in their offspring while the mutation operator in general only brings in minimum such variations. As a result, in this work, the neighbourhood search is labelled as crossover (Yamada and Nakano 1995).

Mutation operator

The primary purpose of performing mutation is to inject variation into a population, to help bring back some essential genetic traits and to avoid pre-mature convergence caused by the existence of some super chromosomes. In this work, as any change in a gene will bring about a series of changes in the genes in the same column, a column-wise changing is introduced to simplify the mutation operation as follows.

(1) Select one column of a chromosome randomly based on the mutation probability, p_m ;

(2) Generate c random numbers $y_1, y_2, \dots, y_c$, $y_i \in [1, 1000], i = 1, 2, \dots, c$;

(3) Use $u_i = y_i / \sum_{i=1}^c y_i$ to form a column; and

(4) Replace the selected column with the new column generated in step 3.

Selection operator

In GA, the way in which a population is generated would affect the survival of fitter chromosomes. In this work, the roulette wheel approach (Goldberg 1989) is used to select

mating chromosomes within the population. Basically, the roulette wheel approach guarantees chromosomes with higher fitness values to occupy a larger slot-size in the roulette wheel. As a result, these chromosomes are more likely to be selected to form the next generation of chromosomes. Such an approach (Figure 4-12) gives every chromosome a chance to propagate as it is based on the probability distribution of fitness values. Alternatively, the elitist selection scheme, which selects the fittest to form the next generation of chromosomes, can also be used together with the roulette wheel selection. It aims at preserving the fittest chromosomes and ensures their survival in the next generation.

Figure 4 - 12 Selection operation for genetic algorithms

Using the aforementioned GA operators as well as the best combination of p_c and p_m obtained from MBEA, the near optimal fuzzy cluster matrix can be determined by the proposed hybrid evolutionary approach.

4.3.5.7 Work Order and Supply Chain Unit Family Formation

The final fuzzy cluster matrix U^* worked out by the MBEA enabled fuzzy c-means specifies the near optimal degree of membership of a work order to a supply chain unit family. Using the matrix, the final work order families and associated supply chain unit families can be obtained.

$$U^* = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{c1} & u_{c2} & \dots & u_{cn} \end{bmatrix} = (u_{ij}) \quad (4-48)$$

If $u_{mj} = \max_{i=1}^c (u_{ij})$, work order j belongs to cluster i .

From Equation 4-39, the cluster centre matrix, V , is the mean value of the attributes of work orders in each supply chain family and v_{li} represents the degree of membership of supply chain units, the attributes, to each work order family. Thus, the final cluster centre matrix V^* is used to form the supply chain unit families.

$$V^* = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1c} \\ v_{21} & v_{22} & \dots & v_{2c} \\ \dots & \dots & \dots & \dots \\ v_{p1} & v_{p2} & \dots & v_{pc} \end{bmatrix} = (v_{li}) \quad (4-49)$$

If $v_{ln} = \max_{i=1}^c (v_{li})$, supply chain unit l belongs to cluster i .

4.3.6 Examples and Discussions

Two sets of sample data were used to examine the existence of the compromised p_c and p_m suggested by the exact schema theorem. Example 1 examines a 10x10 Supply_Matrix with an optimal number of cluster centres of 3. Example 2 further investigates the effect of the suitable compromised GA parameters, p_c and p_m , using a data set gleaned from literature.

Two types of simulation runs have been carried out using the software programs developed by the author, namely a basic GA simulation (SIM1) with one GA population and a MBEA enabled fuzzy c-means (SIM2) with four different GA populations. The parameters for each of the simulation runs are summarized in Table 4-2. The total number of GA generations is 200 and the GA parameters are updated every 20 generations in SIM2. In order to make a fair comparison, the population size for SIM1 is fixed at 200 while SIM2 50 but with four

populations at any time. Thus, the projected population size of SIM2 is 200 (50×4), which is the same as that of SIM1. In the examples, all the simulation runs are able to reach the near optimal solution, an optimal Supply_Matrix easily.

Table 4 - 2 Parameters used in simulation runs

Parameters	SIM1	SIM2	Description
Number_of_generation_for_parameter_updating	NA	20	Number of GA generations between two consecutive TS for parameter updating
FC_c	3	3	number of cluster of fuzzy c-means
FC_m	1.25	1.25	number of m of fuzzy c-means
GA_number_of_generation	200	200	Total number of GA generations
GA_population_size	200	50	GA population size
GA_crossover_rate	0.8	Dynamic	GA crossover probability P_c
GA_mutation_rate	0.05	Dynamic	GA mutation probability P_m
GA_Pc (Max/Min P_c)	NA	0.9/0.4	The maximum and minimum P_c
GA_Pc_Step ($s_c^{\max} / s_c^{\min}$)	NA	0.1/0.05	Crossover probability step length
GA_Pm (Max/Min P_m)	NA	0.15/0.01	The maximum and minimum P_m
GA_Pm_Step ($s_m^{\max} / s_m^{\min}$)	NA	0.03/0.01	Mutation probability step length
GA_elitist_rate	0.08	0.08	Percentage for GA elitist strategy
TS_number_of_individual	NA	4	Number of GA populations for TS
TS_new_population_elitist_rate	NA	0.2	Percentage of the best chromosome to be selected into the new population after TS parameter updating
TS_length_of_tabu_list	NA	8	Tabu list length
TS_promise_level_weightage (best/average)	1/0	0.8/0.2	The weightages for best and average fitness values for promise level calculation respectively

Notes: NA – not applicable

An explanation of the parameters can be found in Section 4.3.5

Based on past experiments, 20 simulation runs is conducted for both SIM1 and SIM2. A comparative analysis based on the mean fitness value and the best individual in each generation of the 20 simulation runs is then performed using Equations 4-50 to 4-53.

$$F_i^- = \frac{1}{n} \sum_{j=1}^n \bar{F}_{ij} \quad (4-50)$$

$$F_i^{*-} = \frac{1}{n} \sum_{j=1}^n \min(F_{ij}) \quad (4-51)$$

$$F_i^* = \min(F_{ij}) \quad (4-52)$$

$$|F_i^*| = F_i^{*S1} - F_i^{*S2} \quad (4-53)$$

where

<i>SIM1</i>	<i>The simulation runs of a basic GA.</i>
<i>SIM2</i>	<i>The simulation runs of the proposed MBEA enabled fuzzy c-means.</i>
<i>n</i> :	<i>The number of simulation runs of SIM1 or SIM2. Here it is 20.</i>
F_{ij} :	<i>The fitness value of generation i of simulation run j of SIM1 or SIM2.</i>
$\bar{F}_{ij}$:	<i>Mean fitness value of generation i of simulation run j of SIM1 or SIM2.</i>
F_i^- :	<i>Mean fitness value of generation i of simulation runs of SIM1 or SIM2.</i>
F_i^{*-} :	<i>The mean value of the best fitness value of generation i of simulation runs of SIM1 or SIM2.</i>
F_i^* :	<i>The best fitness value of generation i of simulation runs of SIM1 or SIM2.</i>
$ F_i^* $	<i>Absolute difference of F_i^*.</i>
F_i^{*S1}	F_i^* of SIM1.
F_i^{*S2}	F_i^* of SIM2.

4.3.6.1 Example 1: a 10x10 Supply_Matrix

The 10x10 Supply_Matrix is given in Table 4-3. It shows the optimal result which has three cluster centres. Subsequently, five pairs of columns or rows of the table were randomly selected and their positions were swapped. For example, columns *su1* and *su9*, and subsequently, rows *wo6* and *wo8* are swapped to form a ‘new’ table. After such an operation, the information registered in the ‘new’ table is used as inputs for the evaluation.

In all the simulation runs, the optimal cluster allocation shown in Table 4-3 can be reached. A comparison of the mean fitness values (F_i^-) and the mean of the best fitness value (F_i^{*-}) obtained in 20 simulation runs using the MBEA enabled fuzzy c-means and the basic GA are shown in Figures 4-13 and 4-14 respectively. It is apparent that the MBEA enabled fuzzy c-means has a faster convergence rate compared to that of the basic GA and the F_i^- (Figure 4-13) and F_i^{*-} (Figure 4-14) are kept well below that of the basic GA except for the first 20 generations. It is due to i) the compromised GA parameter set has not yet been computed before 20th generation as the updating of GA parameter set by TS is defined at every 20 GA

generations starting from 20th generation; and ii) each population of MPSS has a population size of 50 which is much smaller than that of the basic GA with the population size of 200. An obvious decrease in the mean fitness value can be found for every 20 generations as that is the point where the MBEA updates the GA parameter set and creates new populations having the best 20 percent populations in the previous four GA populations. It also demonstrates the effectiveness of the MBEA enabled fuzzy c-means.

Table 4 - 3 Supply_Matrix 1

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>wo1</i>	1	1	1	0	0	0	0	0	0	0
<i>wo2</i>	1	1	1	0	0	0	0	0	0	0
<i>wo3</i>	1	1	1	0	0	0	0	0	0	0
<i>wo4</i>	0	0	0	1	1	1	0	0	0	0
<i>wo5</i>	0	0	0	1	1	1	0	0	0	0
<i>wo6</i>	0	0	0	1	1	1	0	0	0	0
<i>wo7</i>	0	0	0	0	0	0	1	1	1	1
<i>wo8</i>	0	0	0	0	0	0	1	1	1	1
<i>wo9</i>	0	0	0	0	0	0	1	1	1	1
<i>wo10</i>	0	0	0	0	0	0	1	1	1	1

Note: wo_i and su_i denote work orders and supply chain units respectively

Figure 4 - 13 Mean fitness value F_i^- of SIM1 and SIM2 for Example 1

The best fitness value for each generation (F_i^*) is presented in Figure 4-15. It shows the trends exhibited by both MBEA enabled fuzzy c-means and the basic GA. The absolute difference of F_i^* of the MBEA enabled fuzzy c-means is smaller than that of the basic GA after 20th generation. Similar results, i.e. the MBEA enabled fuzzy c-means outperforms the

basic GA, can be deduced from the plots of F_i^* (Figure 4-15) and the absolute difference of F_i^* (Figure 4-16).

Figure 4 - 14 Mean of the best fitness value F_i^{*-} of SIM1 and SIM2 for Example 1

Figure 4 - 15 Best fitness value F_i^* of SIM1 and SIM2 for Example 1

Figure 4 - 16 Absolute difference of the best fitness value F_i^* of SIM1 and SIM2 for Example 1

4.3.6.2 Example 2: a 19x11 Matrix Data Set

The existence of the compromised p_c and p_m was further examined using a 19x11 data matrix which has the same format as a Supply_Matrix (Table 4-4) extracted from the work of Bedworth *et al.* (1991). As virtual clustering of supply chain units is derived from that of group technology, it is reasonable to use a Supply_Matrix that is adapted from a machine cell formation matrix to illustrate the concept. Different from Example 1, Example 2 possesses some exceptional points such as elements $wo12su4$ and $wo6su5$ in the matrix. They are not able to be allocated appropriately to a particular cluster. The parameters used¹ in this example are the same as those employed in Example 1 except for the number of GA generation in both simulation runs (SIM1 and SIM2) is 400 instead of 200 as both SIM1 and SIM2 were not able to reach the optimal clusters within 200 generations. By increasing the number of GA generation from 200 to 400, all the simulation runs were able to find out the optimized clusters as shown in Table 4-5.

Table 4 - 4 19x11 matrix from Bedworth *et al.* (1991).

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>	<i>su11</i>
<i>wo1</i>	0	1	0	1	0	1	0	0	0	0	0
<i>wo2</i>	1	0	0	1	0	1	0	1	0	0	0
<i>wo3</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo4</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo5</i>	0	0	0	0	0	0	1	0	0	1	1
<i>wo6</i>	0	0	0	1	1	0	0	0	1	0	0
<i>wo7</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo8</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo9</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo10</i>	0	1	0	1	0	1	0	1	0	0	0
<i>wo11</i>	1	0	0	1	0	1	0	1	0	0	0
<i>wo12</i>	0	0	0	1	1	0	1	0	1	0	0
<i>wo13</i>	0	0	0	0	0	0	1	0	0	1	1
<i>wo14</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo15</i>	0	0	0	1	0	0	0	0	0	0	0
<i>wo16</i>	0	1	0	0	0	0	0	0	0	0	0
<i>wo17</i>	0	0	0	0	0	0	1	0	0	0	0
<i>wo18</i>	0	0	0	1	0	0	0	1	0	0	0
<i>wo19</i>	0	0	0	1	0	0	1	0	0	0	0

Note: wo_i and su_i denote work orders and supply chain units respectively

Similar to Example 1, the performance measurements of the algorithms are shown in Figures

¹ Please refer to Table 4-2.

4-17 to 4-20. Clearly, the MBEA outperforms the basic GA in terms of the mean fitness value, the best fitness value and the absolute difference of F_i^* . As shown in Figures 4-17 and 4-18, the values of F_i^- (Figure 4-17) and F_i^{*-} (Figure 4-18) of the MBEA enable fuzzy c-means are kept well below those of the basic GA. The value of F_i^* (Figure 4-19) and the absolute difference of F_i^* (Figure 4-20) also display similar trends in terms of performance.

Table 4 - 5 Optimized Clusters for Example 2

	<i>su5</i>	<i>su7</i>	<i>su10</i>	<i>su11</i>	<i>su3</i>	<i>su4</i>	<i>su9</i>	<i>su1</i>	<i>su2</i>	<i>su6</i>	<i>su8</i>
<i>wo5</i>	0	1	1	1	0	0	0	0	0	0	0
<i>wo12</i>	1	1	0	0	0	1	1	0	0	0	0
<i>wo13</i>	0	1	1	1	0	0	0	0	0	0	0
<i>wo17</i>	0	1	0	0	0	0	0	0	0	0	0
<i>wo19</i>	0	1	0	0	0	1	0	0	0	0	0
<i>wo3</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo4</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo6</i>	1	0	0	0	0	1	1	0	0	0	0
<i>wo7</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo8</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo9</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo14</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo15</i>	0	0	0	0	0	1	0	0	0	0	0
<i>wo1</i>	0	0	0	0	0	1	0	0	1	1	0
<i>wo2</i>	0	0	0	0	0	1	0	1	0	1	1
<i>wo10</i>	0	0	0	0	0	1	0	0	1	1	1
<i>wo11</i>	0	0	0	0	0	1	0	1	0	1	1
<i>wo16</i>	0	0	0	0	0	0	0	0	1	0	0
<i>wo18</i>	0	0	0	0	0	1	0	0	0	0	1

Note: wo_i and su_i denote work orders and supply chain units respectively

Figure 4 - 17 Mean fitness value F_i^- of SIM1 and SIM2 for Example 2

In this example, the tabu search used in MBEA enabled fuzzy c-means of SIM2 tends to select a lower crossover probability especially when they are close to convergence. In other words, using the MBEA, the crossover and mutation rates can be made adaptive to suit different stages of search. In so doing, it significantly reduces the computational time as the search evolves. Thus, the MBEA enabled fuzzy c-means is not only able to reach a better solution, but is also likely to reduce computational time as a lower crossover probability is often selected.

Figure 4 - 18 Mean of the best fitness value F_i^{*-} of SIM1 and SIM2 for Example 2

Figure 4 - 19 Best fitness value F_i^* of SIM1 and SIM2 for Example 2

Throughout the two examples and simulation runs, it can be seen that the proposed hybrid

evolutionary approach, MBEA enabled fuzzy c-means, outperforms the basic GA. This was made possible by searching for the suitable compromised pair of p_c and p_m that was suggested in the study of the exact schema theorem. The results of the two examples also reveal the effectiveness of the MBEA enabled fuzzy c-means as it is able to reach the optimal cluster allocations within a reasonable number of GA generations.

Figure 4 - 20 Absolute difference of the best fitness value F_i^* of SIM1 and SIM2 for Example 2

4.4 Summary

This chapter presents the details of a Supply_Graph, which can be used to represent a supply chain. The Supply_Graph can be employed to represent the complex work order routings and business processes from customer orders to suppliers. It has been shown that the Supply_Graph is able to provide an enabling representation, which is generic, flexible and sophisticated enough to incorporate important supply chain features. These features include i) multiple level assembly; ii) various modes of transportation; iii) multiple split and merge of orders; iv) alternative locations or manufacturing sites for product and its components; v) cross boundary representation; and vi) other complex relationship that can be expressed by logical symbols to facilitate supply chain coordination and global schedule optimization.

The rules to extract routings and to convert the Supply_Graph into a part-machine-formation

like matrix, Supply_Matrix, have been proposed. Such a matrix helps in channelling the data from Supply_Graph into both RSO and SCVC modules. It is followed by an investigation into the exact schema. The proposed exact schema theorem attempts to mathematically characterize the evolution of a population of GAs. It is able to predict the expected number of copies of schemas in the next generation. The work further analyzes the crossover probability (p_c) and mutation probability (p_m) using the proposed exact schema theorem and the theory of extrema of functions of several variables. It shows that optimal p_c and p_m do not exist in most cases. As a result, a compromised pair of p_c and p_m can help improve the performance of GAs.

Furthermore, a MBEA enabled fuzzy c-means, which can simultaneously search for the compromised pair of p_c and p_m , to a Supply_Matrix is then proposed. The hybrid approach embeds TS into a GA and is able to dynamically search for better GA parameters in a GA run. Three types of new crossover operations, namely partial exchange, overall exchange and neighbourhood search, have been proposed. The evaluation of the fitness value and the promise level has also been formulated. The MBEA enabled fuzzy c-means enables p_c and p_m to be adaptive so as to suit different stages of the GA search for near optimal solutions.

Finally, two examples were conducted to illustrate the existence of the compromised p_c and p_m with the aid of the proposed MBEA enabled fuzzy c-means. In these examples, the influence of p_c and p_m on, respectively, a 10x10 and a 19x11 matrices have been evaluated. The results show that a compromised pair of GA parameters can be found. By using the compromised pair of GA parameters, the MBEA enabled fuzzy c-means was able to reach better solutions faster as a result of a faster convergence rate.

Chapter 5 MBEA ENABLED ROUTING AND SEQUENCE OPTIMIZATION OF A SUPPLY CHAIN

5.1 Introduction

Section 3.2 described a framework for extended supply chain coordination and optimization. As one of the key modules, the routing and sequence optimizer (RSO) generates a preferred set of routing, transportation and work order process plan based on various constraints, such as customer service level, cycle time, and cost and so on. The result obtained can be further channelled to the SCVC module for supply chain clustering. As mentioned in Section 3.4, MBEA, a novel hybrid approach developed in this work, can be used to solve the routing and sequence optimization problem. The architecture of the MBEA has been discussed in Section 3.4. In Chapter 4, fuzzy c-means was incorporated into MBEA to handle the Supply_Matrix problem that was used to study the proposed exact schema theorem and GA parameters. The results presented in Section 4.3.6 show that MBEA is able to find a set of compromised GA parameters which are able to improve the performance of GA. In this chapter, the MBEA is further tuned to solve the routing and sequence optimization problem.

5.2 Heuristic of Routing and Sequence Optimization for a Supply Chain

As mentioned in Section 2.1, in a typical supply chain, customers, suppliers, warehouses, manufacturing plants and other units in the supply chain may be geographically distributed (Figure 2-1). A work order may have multiple routings that denote materials flows. It is assumed that materials flow captures the sequence in which materials move from suppliers (raw materials) to manufacturers (intermediate product), and to customers (finished product)

through the distribution network as depicted in Figure 5-1.

Figure 5 - 1 Multiple routings of a supply chain

For each routing of a work order, it may use different materials, and goes through different manufacturing plants. Because of this, the work order may have different cycle times, different costs and delivery dates when applying different routings. In other words, these routings have different

- Materials/manufacturing/transportation/inventory/delivery cost;
- On time delivery;
- Cycle time and so on.

The purpose of the RSO module is to search for a preferred set of routing, transportation and work order process plan that is effective in maintaining or even increasing customer service level, reducing inventory, transportation and production costs, and eventually lowering safety stock level within the limit of the capacity of each supply chain unit.

5.2.1 Problem Definition

A general supply chain routing and sequence optimization problem may be represented using a Supply_Graph (Section 4.2) as follows.

$$G = G_1 \cup G_2 \cup G_3 \cup \dots \cup G_m$$

$$G_i = \{N_i, A_i, L_i\}$$

where:

G : *Supply_Graph.*

G_i : *Supply_Graph for work order i .*

N_i : *Nodes involved in processing work order i .*

A_i : *Arcs involved in processing work order i .*

L_i : *Logical relationship in processing work order i .*

m : *Number of work orders.*

n : *Number of nodes.*

k : *Number of arcs.*

$N = \{n_1, n_2, \dots, n_n\}$: *Entire set of nodes.*

$A = \{a_1, a_2, \dots, a_k\}$: *Entire set of arcs.*

Using the Supply_Graph, a supply chain routing selection problem can be translated to finding a routing combination $G^* = G_1^* \cup G_2^* \cup G_3^* \cup \dots \cup G_m^*$ such that it optimizes some performance measures, such as customer service level and cost. In this work, cost is used as the key performance measure. Hence, the objective is to minimize cost while maximize on-time delivery. Accordingly, the objective function is given as follows:

$$f = \min(r^c C^p + r^d n^l \frac{C^p}{m}) \quad (5-1)$$

where

f : *Fitness value.*

C^p : *Cost of the plan.*

n^l : *Number of late orders of the plan.*

m : *Total number of orders.*

r^c : *The weight of cost.*

r^d : *The weight of penalty on late orders.*

5.2.2 The Heuristic of Routing and Sequence Optimizer (RSO)

Figure 5 - 2 System structure of routing and sequence optimizer (RSO)

As illustrated in Figure 5-2, the RSO module consists of the following key functional sub-modules.

- (1) **Supply_Graph Routing Extraction.** It retrieves the work order from a Supply_Graph that is under consideration. Using the procedures described in Section 4.2.3, an entire list of routings and transportation modes can be worked out and prepared for the RSO optimization engine.
- (2) **Objective Measurements.** It computes the value attained by the objective function based on Equation 5-1. The measurement can be the costs incurred by delivery, manufacturing and/or distribution, and/or some management level business strategies such as on-time delivery, customer service level or inventory reduction that can be further introduced into the objective function.
- (3) **RSO Optimization Engine.** The RSO optimization engine combines the features of GA and TS to find the near optimal work order routing, transportation mode and order plan. It is further enhanced by the multiple population search strategy of MBEA and possesses the ability to search for the suitable compromised GA parameters that are able to improve the GA performance.
- (4) **RSO Output.** This module takes care of the results worked out by the RSO optimization engine and represents them in a Supply_Matrix format which can be used by the SCVC module for virtual clustering.

Figure 5-3 presents a flow chart of the proposed MBEA enabled RSO. As shown, TS is embedded into the GA to implement the multiple population search strategy (MPSS) of the MBEA. The hybrid approach is able to facilitate the search process, help determine GA parameters and generate next generation of chromosomes, and avoid premature convergence. Basically, the aforementioned routing selection and sequence optimization problem is a minimization problem in nature. Multiple objectives, such as on-time delivery and cost of the product that need to be minimized, are considered in this work.

Similarly, a minimization problem needs to be transformed into a maximization problem in order to apply the GA. The transformation can be easily realized as follows (Goldberg 1989).

$$f(x) = \begin{cases} C_{max} - g(x) & \text{if } C_{max} - g(x) > 0 \\ 0 & \text{otherwise} \end{cases}.$$

Here, $g(x)$ is the objective function and C_{max} can be assigned a value initially or assigned the largest value of $g(x)$ in the current GA population.

Figure 5 - 3 Flow chart of the proposed MBEA enabled RSO

Similar to the MBEA enabled fuzzy c-means procedure adopted in Section 4.3.5, a promise level (Section 5.2.3) needs to be calculated to guide the selection of the compromised GA parameter set. The procedures for searching and updating the GA parameter set and for the generation of neighbourhood parameter set are depicted in Figures 5-4 and 5-5, respectively.

The equations for creating the neighbourhood parameter set are given as follows.

$$s_c = \frac{s_c^{\max} - s_c^{\min}}{2^{n_c}} + s_c^{\min} \quad (5-2)$$

$$s_m = \frac{s_m^{\max} - s_m^{\min}}{2^{n_c}} + s_m^{\min} \quad (5-3)$$

$$N = [(r_c, r_m + s_m), (r_c, r_m - s_m), (r_c + s_c, r_m), (r_c - s_c, r_m)] \quad (5-4)$$

where

- s_c : Length of step of crossover probability to find the neighborhood parameters.
- s_m : Length of step of mutation probability to find the neighborhood parameters.
- r_c : Original crossover probability before the parameter search.
- r_m : Original mutation probability before the parameter search.
- n_c : Counter of the duplication of the parameter set. If the same parameter set as the last run is chosen, $n_c = n_c + 1$; otherwise, $n_c = n_c - 1$.
- $s_c^{\max}$: Predefined maximum length of step of the crossover probability.
- $s_c^{\min}$: Predefined minimum length of step of the crossover probability.
- $s_m^{\max}$: Predefined maximum length of step of the mutation probability.
- $s_m^{\min}$: Predefined minimum length of step of the mutation probability.
- N : Neighborhood parameter set collection.

Figure 5 - 4 Flow chart of searching and updating GA parameters for RSO

Figure 5 - 5 Flow chart of neighborhood creation for RSO

5.2.3 Fitness Evaluation and Promise Level Calculation

The fitness or the relative fitness of chromosomes needs to be evaluated in order to select chromosome pairs for genetic operations. The evaluation process includes fitness calculation,

scaling and ranking. Management-level strategies can be incorporated into the objective functions for the purpose of fitness evaluation. In this study, two factors, namely cost and on-time delivery, are considered. The formulae for the evaluation are given as follows.

$$C^p = \sum_{i=1}^m (C_i^S + C_i^M + C_i^D) \quad (5-5)$$

$$f = r^c C^p + r^d n^l \frac{C^p}{m} \quad (5-6)$$

where

- f : Fitness value.
 C^p : Cost of the plan.
 n^l : Number of late jobs of the plan.
 m : Total number of work orders.
 r^c : The weight of cost.
 r^d : The weight of penalty on late orders.
 C_i^S : Supplier's delivery cost.
 C_i^M : Manufacturing cost.
 C_i^D : Distribution centre cost.

The promise level of a parameter set for a population can be derived using the formulae listed as follows.

$$f_{km}^{best} = \min(f_{kmi}) \quad (5-7)$$

$$f_{km}^{avg} = \frac{\sum_{i=1}^{PopSize} f_{kmi}}{PopSize} \quad (5-8)$$

$$f_{km}'^{best} = \frac{f_{km}^{best} - \min(f_{km}^{best})}{\max(f_{km}^{best}) - \min(f_{km}^{best})} \quad (5-9)$$

$$f_{km}'^{avg} = \frac{f_{km}^{avg} - \min(f_{km}^{avg})}{\max(f_{km}^{avg}) - \min(f_{km}^{avg})} \quad (5-10)$$

$$p_{km} = w_{best} f_{km}'^{best} + w_{avg} f_{km}'^{avg} \quad (5-11)$$

$$w_{best} + w_{avg} = 1 \quad (5-12)$$

where

f_{kmi} : Fitness value of i^{th} chromosome of m^{th} population of k^{th} generation.

PopSize: Population size.

f_{km}^{best} : Relative fitness value of the best chromosome of m^{th} population of k^{th} generation.

f_{km}^{avg} : Relative average fitness value of chromosomes of m^{th} population of k^{th} generation.

P_{km} : Current promise level of GA parameters in of m^{th} population of k^{th} generation.

w_{best} : Weight of the relative fitness of the best chromosome in terms of the fitness value of a population. It is fixed at 0.5 in this research.

w_{avg} : Weight of the average relative fitness of a population. It is fixed at 0.5 at this study.

5.2.4 Chromosome Representation and GA Operators

The GA operators including mutation and selection have been redesigned to be adaptive to the fitness value of the individual chromosome. This can further improve the performance of the GA.

5.2.4.1 Representation

In this work, a routing and sequence, which comprises a series of work orders, can be represented as a chromosome in GA terminology. Each gene of a chromosome stands for a work order. However, because of the precedence of routings of a work order, this kind of chromosome representation may produce infeasible results. To avoid this situation, all the operations of a work order were given the same symbol, work order ID, and then interpreted according to the order of occurrence in the sequence for a given chromosome (Gen and Cheng, 1997). Here, a non-fixed length string is used as a gene to represent the routing and sequence of a work order. There are two parts in the string separated by a colon ':'. The first part is the identification (ID) number of the alternative routings derived from the Supply_Graph G , and the second part is work order ID to identify different work orders. For

example, the gene '4:03' represents the work order '03' and currently the 4th routing in Supply_Graph G is being used.

For an ' m -work order n -supply chain unit' routing and sequence optimization problem, a chromosome contains not more than $n \times m$ genes. This implies that some of the work orders may not need to go through all the supply chain units. For example, Chromosome '1:03-2:02-1:01-2:02-1:01-1:03-1:01' shows that there are altogether three work orders, from '01' to '03', the last two digits of each gene. The first gene '1:03' in the chromosome represents the first handling unit of work order '03' while the second '1:03' denotes the second handling unit of the same work order; the ID number of the alternative routing is '1', which is represented by the first digit of the gene. By mapping the number of work orders and alternative routings to the Supply_Graph and supply chain database, the supply chain unit, materials, lead time, transportation mode and other resources used for each of these work order can be easily determined. Obviously, any permutation of the genes that satisfies the requirements of the routing and sequence optimization problem always yields a feasible solution.

5.2.4.2 Crossover Operator

Partial crossover operation, which involves partial schedules of two parents, is used here to exchange the ordering of chromosomes. Since these partial schedules contain different types of genes, the offspring generated can be illegal. Thus, a novel repair operation is carried out immediately after each crossover operation in order to legalize the offspring. As the representation of a chromosomes is context-dependent and the offspring generated need to inherit the genetic traits of their respective parents, the partial schedule in each of the offspring must therefore has the same ordering as their parents. Otherwise, the genes in the partial schedule may refer to different operations. The procedure for the crossover operation is given as follows.

- (1) Choose a partial string in every parent randomly;
- (2) Exchange the selected genes in the two parents; and
- (3) Delete or add genes to legalize the offspring, that is, order the selected genes in the offspring similar to those of their parents, so as to inherit the genetic traits of their parents.

5.2.4.3 Mutation Operator with Adaptive Mutation Probability

The primary purpose of mutation is to introduce variation into a population, to help bring back some essential genetic traits and to avoid pre-mature convergence caused by the existence of some super chromosomes. Here, a work order-pair exchange scheme that involves swapping of two randomly selected genes is used as the mutation operator. For example, '1:03-2:02-1:01-2:02-1:01-1:03-1:01' is the chromosome chosen to mutate. Two genes ('1:03' and '2:02') are randomly selected and swapped to create the offspring, in this case, '2:02-1:03-1:01-2:02-1:01-1:03-1:01'. In order to introduce alternative routings, a secondary mutation operator is proposed as follows.

- (1) Create lists of ID numbers of alternative routings of a work order;
- (2) Randomly select one gene (one work order) from the chromosome;
- (3) Randomly select a ID number from the list of the ID numbers of the alternative routings of the work order chosen in Step 2; and
- (4) Change the first portion (represents the ID number of alternative routing) of all the genes, which represents the same work order as the one selected in Step 2, to the selected ID number of alternative routing in Step 3. This completes the mutation process.

Furthermore, in order to avoid early convergence, fitter chromosomes are given lower mutation probability, while weaker chromosomes are given higher mutation probability so as to promote the exploration of search space beyond local area (Figure 5-6). The following formulae are for the computation of adaptive mutation probability.

$$f'_{kmi} = \frac{\max(f_{km}) - f_{kmi}}{\max(f_{km}) - \min(f_{km})} \quad (5-13)$$

$$p^m_{kmi} = p^m_{km} r^m + (1 - r^m) f'_{kmi} p^m_{km} \quad (5-14)$$

where

f_{kmi} : Fitness value of i^{th} chromosome of m^{th} population of k^{th} generation.

f'_{kmi} : Relative fitness value of i^{th} chromosome of m^{th} population of k^{th} generation.

p^m_{km} : Mutation probability of m^{th} population of k^{th} generation.

p^m_{kmi} : Mutation probability of i^{th} chromosome of m^{th} population of k^{th} generation.

r^m : Ratio of the mutation probability of the best chromosome to p^m_{km} . It is set to 0.5 that indicates a mutation probability of the best chromosome to half of p^m_{km} .

k : GA Generation number.

m : Population number in a generation.

Figure 5 - 6 Flow chart of calculation of the mutation probability for RSO

5.2.4.4 Reactive Selection Operator

As already mentioned, the way in which a population is generated would affect the survival of fitter chromosomes. In this work, the roulette wheel approach (Goldberg 1989) is used to select the mating chromosomes within the population. As previously explained, the roulette wheel approach guarantees chromosomes with higher fitness values to occupy a larger slot-size in the roulette wheel. As a result, these chromosomes are more likely to be selected to

form the next generation of chromosomes. Such an approach gives every chromosome a chance to propagate as it is based on the probability distribution of fitness values. Alternatively, the elitist selection scheme, which selects the fittest to form the next generation of chromosomes, can also be used. It aims at preserving the fittest chromosomes and ensures their survival in the next generation.

Figure 5 - 7 Flow chart of GA selection for RSO

Accordingly, population selection is subject to:

$$s_{km} \leq s_p \quad (5-15)$$

where

s_p : *Predefined Population similarity ranges from 0 to 1.*

s_{km} : *Population similarity of m th population of k th generation.*

Between the two consecutive populations, there may exist n_s similar chromosomes. Since a higher n_s value is likely to bring about premature convergence, a so-call population similarity measure, which is given by n_s /population size, is proposed and used to control the similarity of two consecutive populations (Figure 5-7). For each population, its population similarity is not allowed to exceed s_p . Basically, population similarity is adaptive and changes according to the number of GA generations with smaller value at the beginning of a GA run to maintain population diversity, and larger value at the end of the GA run to facilitate convergence.

5.3 Examples and Discussions

The functional structure of the RSO module developed is shown in Figure 5-8. Data such as customer orders, the supply chain model, and the production capacity and cost can be imported from files or manually through the *data input* function. The configurations of the optimization engine, GA, TS, MBEA and their related parameters can be defined using the *system configuration* function. This includes the constraints and objective functions that are required by the optimization engine. The *RSO optimizer* accesses the configuration data and works out the near optimal work order routing, transportation mode and order plan. The user can control the running of the *RSO optimizer* and monitor the status and the progress of the optimization engine through the *RSO engine control* and the *runtime monitor*. The *RSO result output* function provides the routing and work order process sequence. Besides, statistic data are stored for future reference.

Figure 5 - 8 Functional structure of the prototype RSO

5.3.1 Example 1: a Basic Model

5.3.1.1 Model Description

Figure 5-9 shows a supply chain model, which comprises three suppliers, three manufacturing plants, two assembly plants, three distribution centres and the end customer. Raw materials are delivered from the suppliers, transformed into half-finish components by the manufacturing plants and assembled to commercial products in the assembly plants, transported to DCs, and ultimately, delivered to customers. The detailed data model is adapted from literatures including those of Bhatnagar and Sohal (2005), Caramanis and Anh (1999), Leung *et al.* (2002), and Robinson and Bookbinder (2007).

Tables 5-1 to 5-4 depict the delivery lead-time and cost relationship, production capacity, lead-time and cost relationship, DCs' capacity, lead-time and cost relationship, and orders to be processed of the basic model for the study of the prototype system.

Figure 5 - 9 A supply chain model for study

Table 5 - 1 Suppliers' delivery lead-time and cost

Supply chain unit	Supplier Cap	Delivery time (day)	Delivery cost (unit cost)
Supplier 1	200	10	10
Supplier 2	150	6	12
Supplier 3	180	4	12

The suppliers' delivery lead-time and the related cost are depicted in Table 5-1. In recent years, the distance between two destinations is less critical compared to the transportation

mode such as by sea freight or by air freight, it is assumed that the delivery lead-time and cost are independent of destination in this study. For example, Supplier 1 takes 10 days to deliver its materials to the customer, the manufacturing plants, regardless where the customer is located. It is assumed that it costs 10 units to do so, while Supplier 2 takes less time (6 days) but delivery costs more (say 12 units).

Table 5 - 2 Production lead-time and cost

Supply chain unit	No. of lines	Production lead-time (day)					Production cost per day (unit cost)				
		P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Mfg Plant 1	3	5	8	6	10	10	7.2	14.4	21.6	4.8	12
Mfg Plant 2	2	8	15	15	15	6	4.8	4.8	7.2	2.4	21.6
Mfg Plant 3	1	10	11	12	6	15	2.4	9.6	12	9.6	7.2
Assy Plant 1	2	10	14	6	9	6	24	7.2	21.6	4.8	19.2
Assy Plant 2	3	15	6	12	16	10	12	21.6	9.6	2.4	9.6

Table 5 - 3 Distribution centre capacity, lead-time and cost

Supply chain unit	Capacity	Lead time (day)	Cost per day (unit cost)
DC1	100	3	2.4
DC2	200	3	7.2
DC3	150	3	7.2

Table 5-2 illustrates the production lead-time and cost. All the plants including the manufacturing plants and the assembly plants produce five types of products, P1, P2, P3, P4 and P5. In this study, there are three manufacturing lines in Manufacturing Plant 1. For each line, it needs 5 days to complete product P1 and 8 days for P2, and the respective costs per day are 7.2 units and 14.4 units.

Besides the lead-time and cost of processing the shipment and delivery, the capacity is embedded in the distribution centre model (Table 5-3). It is assumed that DC1 has a capacity of handling 100 units of products at any time while DC2 has a higher capacity of 200 units. As DC2 and DC3 provide better services, for example, they are able to maintain consistent temperature and humidity level in the store room, and cost 7.2 units per day which is 3 times of that of DC1 although the lead-times are actually the same.

Fifteen (15) orders of different products are processed (Table 5-4). The order quantity and the respective due date are also shown in the table. The order planning start date is fixed on 10 Jan of 2000 for all the simulation runs.

Table 5 - 4 Orders to be processed

Order	Product	Customer	Order qty	Due date
A001	P1	ABC Engineers	20	2000-02-21
A002	P1	MDN Gearboxes	30	2000-03-05
A003	P1	ABC Engineers	20	2000-02-25
B001	P2	MDN Gearboxes	30	2000-02-28
B002	P2	A1 Axles	40	2000-03-05
B003	P2	MDN Gearboxes	30	2000-03-10
C001	P3	A1 Axles	10	2000-02-15
C002	P3	Central Tubes	50	2000-02-10
C003	P3	A1 Axles	20	2000-02-21
D001	P4	Central Tubes	25	2000-03-10
D002	P4	ABC Engineers	30	2000-02-15
D003	P4	Central Tubes	15	2000-03-15
E001	P5	MDN Gearboxes	45	2000-02-25
E002	P5	ABC Engineers	50	2000-02-28
E003	P5	ABC Engineers	35	2000-03-15

5.3.1.2 Results and Discussions

Two types of simulation runs have been carried out, namely a basic GA simulation (SIM1) and a MBEA enabled RSO (SIM2). The parameters for each of the simulation runs are summarized in Table 5-5.

Similarly, in order to make a fair comparison, the population size for SIM1 is fixed at 200 while SIM2 50 but with four populations at any time. Thus, the projected population size of SIM2 is 200 (50×4), which is the same as that of SIM1. The crossover probability and mutation probability are 0.8 and 0.005 respectively for SIM1, as from the preliminary simulation runs carried out by the author, this parameter set generates the best solution for the basic GA. Dynamic crossover and mutation probabilities are applied in SIM2 using MBEA. As depicted in Table 5-5, $s_c^{\max}$, $s_c^{\min}$, $s_m^{\max}$ and $s_m^{\min}$ are fixed at 0.2, 0.01, 0.05 and 0.001

respectively, which restrict the steps of the crossover probability between 0.01 and 0.2, and mutation probability between 0.001 and 0.05.

Table 5 - 5 Parameter setting of SIM1 and SIM2

Parameters	SIM1: Basic GA	SIM2: MBEA enabled
Number of simulation runs	20	20
Number of generation for parameter updating	NA	10
Generation of new population	NA	Random selection plus elitist 30%
Number of population	1	4
Number of GA generation	100	100
Population size	200	50
Initial crossover probability	0.8	0.9
Initial mutation probability	0.005	0.01
Elitist strategy (percentage of the best individual to be selected)	8%	8%
Crossover probability step length ($s_c^{\max} / s_c^{\min}$)	NA	0.2 / 0.01
Mutation probability step length ($s_m^{\max} / s_m^{\min}$)	NA	0.05 / 0.001
Weight of Delivery on time	2	2
Weight of order cost	1	1
Length of Tabu list of GA parameters	NA	5

Note: NA – not applicable

The comparison is based on the mean fitness value and the best individual in each generation of the 20 simulation runs. It can be derived by the following formulae:

$$F_i^- = \frac{1}{n} \sum_{j=1}^n \bar{F}_{ij}$$

$$F_i^{*-} = \frac{1}{n} \sum_{j=1}^n \min(F_{ij})$$

where

n : The number of simulation runs of SIM1 or SIM2. Here it is 20.

F_{ij} : The fitness value of generation i of simulation run j of SIM1 or SIM2.

$\bar{F}_{ij}$: Mean fitness value of generation i of simulation run j of SIM1 or SIM2.

F_i^- : Mean fitness value of generation i of simulation runs of SIM1 or SIM2.

F_i^{*-} : The mean value of the best fitness value of generation i of simulation runs of

SIM1 or SIM2.

The work order routings generated by both SIM1 and SIM2 are evenly distributed to all the supply chain units in most simulation runs. It is able to maximize the on-time delivery. However, the fitness values vary a lot as the objective function includes both on-time delivery and cost.

- Mean fitness value

A comparison of the mean fitness values (F_i^-) is shown in Figure 5-10. It is apparent that the MBEA enabled RSO has a faster convergence rate and F_i^- is kept 100 to 200 below that of the basic GA. The fitness values of the first five generations possess noticeable differences (Figure 5-11). The reason being 10% of chromosomes with better fitness value are introduced to each population initially. Only one population is used in SIM1 compared to four different populations in SIM2.

Figure 5 - 10 Mean fitness value F_i^- of SIM1 and SIM2 for Example 1

The plot of the standard deviation of the mean fitness value (Figure 5-12) reveals that the variation of individuals of MBEA enabled RSO is smaller than that of the basic GA. This also implies that the MBEA enabled RSO requires fewer generations to converge. Only the first five generations show contradictory trend due to initial setting.

Figure 5 - 11 Absolute difference of mean fitness value F_i^- of SIM1 and SIM2 for Example 1

Figure 5 - 12 Standard deviation of mean fitness value F_i^- of SIM1 and SIM2 for Example 1

- Best fitness value

The mean value of the best fitness value for each generation (F_i^{*-}) is shown in Figures 5-13 to 5-16, while Figure 5-17 presents the absolute difference of the best fitness value for each generation in all the simulation runs. Similar conclusion, i.e. the MBEA enabled RSO outperforms the basic GA, can be drawn from the observation of the plots of the F_i^{*-} , the absolute difference of F_i^{*-} and the standard deviation.

During the simulation runs, the MBEA enabled RSO arrives at the best solution, which has a fitness value of 4697, in 28 generations, while the basic GA reaches the same solution in 50

generations (Figure 5-17). It is obvious that the MBEA enabled RSO can converge earlier. This can be attributed to the application of adaptive crossover and mutation rates.

Figure 5 - 13 Mean of the best fitness value F_i^{*-} of SIM1 and SIM2 for Example 1

Figure 5 - 14 Absolute difference of F_i^{*-} of SIM1 and SIM2 for Example 1

Figure 5 - 15 Standard deviation of mean of F_i^{*-} of SIM1 and SIM2 for Example 1

Figure 5 - 16 Absolute difference of Standard deviation of F_i^{*-} of SIM1 and SIM2 for Example 1

Figure 5 - 17 Absolute difference of the best fitness value of SIM1 and SIM2 for Example 1

Figure 5-18 shows a typical solution of the preferred routings of orders, which can minimize the cost and maximize the on-time delivery. For example, it shows that Order A003 is planned to get the materials from Supplier 1. After processing by Manufacturing Plant 3 and Assembly Plant 2, the final product is transported to DC1 before delivery to customer. Both SIM1 and SIM2 are able to derive similar results. However, the minimum and the mean total cost of orders shown in Figures 5-19 and 5-20, respectively, reveal that the MBEA enabled RSO has a higher convergence rate as it is able to reach the optimal value much faster than

the basic GA. On time delivery in terms of the number of late orders that fail to be delivered to customer by due date is also plotted (Figure 5-21). From the figure, it is apparent that more late orders can be found in the first five to ten generations. Once MBEA is instantiated, the number of “late jobs” diminishes quickly.

Figure 5 - 18 Results for Example 1

Figure 5 - 19 Minimal total cost of orders of SIM1 and SIM2 for Example 1

Figure 5 - 20 Mean total cost of orders of SIM1 and SIM2 for Example 1

Figure 5 - 21 Mean number of late orders of SIM1 and SIM2 for Example 1

Furthermore, the basic model has been extended by including multiple suppliers and large number of supply chain units in Examples 2 and 3 respectively. This is to illustrate the effectiveness of the proposed MBEA enabled algorithm in solving more complex RSO

problems. In order not to burden the readers with too many figures, the figures that can clearly illustrate the results will be presented

5.3.2 Example 2: a Supply Chain with Multiple Suppliers

Besides the three suppliers mentioned in Example 1, another 21 suppliers have been added in order to examine the effectiveness of the MBEA in handling supply chain routing selection with multiple suppliers. This is done by repeating the three original suppliers seven times so as to form a supply chain with 24 suppliers. The results generated by the basic GA (SIM1) and the MBEA enabled RSO (SIM2) using the same set of parameters (Table 5-5) are shown in Figures 5-22 and 5-23. Similarly, the work order routings generated by both SIM1 and SIM2 are reasonably distributed to all the supply chain units in most simulation runs. The work order routings are not omitted as there are too many supply chain units to show in the result. From the figures, it is apparent that MBEA enabled RSO is able to generate better F_i^{*-} in terms of mean fitness values and best fitness values. The absolute difference of F_i^{*-} as shown in Figure 5-18 increases consistently. This indicates that the MBEA enabled RSO is capable to reach a near optimal solution in fewer generations than the basic GA.

Figure 5 - 22 Absolute difference of Mean of F_i^{*-} of SIM1 and SIM2 for Example 2

The above observation can also be seen in the minimal total cost of orders and the mean total cost of orders as illustrated in Figures 5-24 and 5-25 respectively. The minimal total cost of SIM2 is well below that of SIM1. It has been improved from 4661.48 to 4620.68. The mean total cost decreases much faster for SIM2 and its value is smaller than that of SIM1 after about 40 generations. It shows that the MBEA enabled RSO constantly outperforms the basic GA. As for Example 1, on time delivery can be quickly maximized by the MBEA enabled RSO after the initial 5 to 10 generations (Figure 5-26).

Figure 5 - 23 Absolute difference of the best fitness value of SIM1 and SIM2 for Example 2

Figure 5 - 24 Minimal total cost of orders of SIM1 and SIM2 for Example 2

Figure 5 - 25 Mean total cost of orders of SIM1 and SIM2 for Example 2

Figure 5 - 26 Mean number of late orders of SIM1 and SIM2 for Example 2

5.3.3 Example 3: a Large Supply Chain Routing Selection Problem²

A large supply chain problem is presented in this example. The basic model used in Example

² The prototype SCASO system can also integrate with such simulation programmes as “Beer Game”. In so doing, if at a particular point in time of the Beer Game, all the orders and related supply chain data can be collected and used as the inputs, the prototype SCASO system can be used to work out a proper schedule for all the supply chain components involved in the Game. This is based on the assumption that all the information is shared along the supply chain.

1 is further expanded by adding seven times more of suppliers, three times more of manufacturing plants, assembly plants and distribution centres. Accordingly, this large supply chain model comprises 24 suppliers, 18 manufacturing plants, 15 assembly lines, and 9 distribution centres. The orders in hand are also increased by two folds to reach 45. Same investigations are carried out and the results are shown in Figures 5-27 and 5-28. Similarly, the MBEA enabled RSO outperforms the basic GA in terms of mean fitness values and the absolute difference F_i^{*-} . The mean fitness value has been improved from 14477.9 to 14451.5. As mentioned, smaller mean fitness value and better F_i^{*-} suggest convergence in fewer generations.

Figure 5 - 27 Absolute difference of Mean of the best fitness value F_i^{*-} of SIM1 and SIM2 for Example 3

Figure 5 - 28 Absolute difference of the best fitness value of SIM1 and SIM2 for Example 3

One observation that is not obvious in Examples 1 and 2 concerns the run time of simulation.

Each of the simulation runs of Examples 1 or 2 takes only a few minutes. However, it takes tens of minutes for Example 3 due to the size of the supply chain. The run time of each simulation of SIM1 described in Example 3 appears to change very little as the crossover and mutation rates are fixed at 0.8 and 0.005 respectively. However, large variations are observed in SIM2 as the MBEA creates different and near optimal crossover and mutation rates in every 10 generations. The run time of SIM2 ranges from 25% to 110% of the average run time of SIM1. Many of the simulation runs of SIM2 can be completed much faster than those of SIM1 as the MBEA enabled RSO of SIM2 tends to select a lower crossover probability when they are close to convergence. It proves the findings in Section 4.3.6 that using the MBEA, the crossover and mutation rates can be made adaptive to suit different stages of GA runs. That means the MBEA enabled RSO is not only able to reach a better solution, but also possesses good potential to reduce computational time.

5.4 Summary

The focus of this Chapter is on the routing selection for work orders and the optimization of work order sequencing using an MBEA enabled hybrid heuristic based on GA, TS and MPSS.

Firstly, the framework of the RSO module has been depicted. It includes Supply_Graph routing extraction, objective measurements, RSO optimization engine and RSO output. The RSO module is able to generate a preferred set of routing, transportation and work order process plan based on various constraints, such as customer service level, cycle time, and cost and so on. The result can be further channelled to the SCVC module for supply chain clustering.

Secondly, the MBEA is adapted to realize the optimization engine of RSO for the routing and sequence optimization problem as well as searching for the suitable compromised GA parameters to improve the GA performance. To do so, a novel chromosome representation scheme, new genetic operators to repair illegal chromosomes, adaptive mutation probability

and a reactive selection technique based on population similarity have been proposed and implemented. Through managing multiple populations in a GA run, it has been shown that MBEA can be used to search and update GA parameters dynamically. This is done via a so-called promise level of GA parameter sets.

Finally, three examples were used to illustrate the capability of the MBEA enabled RSO. The results show that compared to basic GAs, the MBEA performs better as it determines the compromised pair of GA parameters for different stage of GA runs. It shows the early convergence and better solutions to the RSO problems. As a result, it is able to find the best solution in fewer generations and possesses good potential to reduce computational time. More suppliers and supply chain units had been introduced in Examples 2 and 3 to show that the algorithm can also handle reasonably complex problems.

Chapter 6 AN EVOLUTIONARY APPROACH TO FUZZY CLUSTERING FOR SUPPLY CHAIN VIRTUAL CLUSTERING

6.1 Introduction

As discussed in Section 3.2, extended supply chain optimization problems are complex and can hardly be solved by conventional algorithms due to combinatory explosion. This chapter described the work that adapted the basic notions of group technology (GT) and applies them to realize a supply chain virtual clustering (SCVC) module. The SCVC module virtually and dynamically organizes the supply chain units, transportation modes and work orders into different unit-transportation-work order families using a MBEA enabled fuzzy clustering approach, which embeds fuzzy c-means, a widely used fuzzy clustering algorithm. In so doing, a complex supply chain model can possibly be decomposed into supply chain families of smaller size. The search space of a complex large-scale supply chain problem can then be drastically reduced. It is envisaged that the efficiency of supply chain optimization can be improved.

The details of the MBEA enabled fuzzy c-means approach to handle Supply_Matrix problem have been presented in Section 4.3.5. One common problem associated with the application of fuzzy c-means is that the clustering parameters such as number of clusters, c , and weighting exponent, m , need to be predetermined. In this chapter, the MBEA enabled fuzzy c-means approach will be adapted to handle SCVC. It will be further enhanced to automatically identify the optimal clustering parameters. The necessity to pre-define suitable values for the parameters c and m of fuzzy c-means (FCM), which may not be known as a prior knowledge, can therefore be eliminated.

6.2 Overview of the Supply Chain Virtual Clustering Module (SCVC)

Figure 6-1 shows the key functional sub-modules of the SCVC module. They are:

- (1) **Supply_Matrix Converter.** It retrieves the *Supply_Graph* and the relevant *Supply_Graph* matrix of each work order and converts it into a *Supply_Matrix* that can be used for virtual clustering. The detail procedures of the converter have been discussed in Section 4.2.3.
- (2) **Performance Measure.** It calculates the validity index of fuzzy c-means and serves as the objective function of TS that is used to determine the performance of different GA populations with different c and m . The measurement can be for inter or intra cluster transportation, the loading balance and/or the group efficiency described in Section 6.3.3.
- (3) **SCVC Optimization Engine.** The engine utilizes the basic notions of GT and combines them with the features of fuzzy c-means, GA and TS to find the near optimal supply chain families. The proposed MBEA enabled SCVC optimization engine is able to search for the suitable compromised fuzzy c-means parameters as well as the near optimal clusters.
- (4) **SCVC Output.** It stores the supply chain unit-transportation-work order families worked out by the SCVC module and feeds them into the SCOS module.

Supported by the SCVC optimization engine, the SCVC is able to organize a complex large-scale supply chain into different supply chain unit-transportation-work order families. It is postulated that work orders can be processed and optimized mainly within the respective families. This facilitates the process of distributed planning and scheduling of SCOS. The above-mentioned approach has the following characteristics.

- (1) **Compartmentalize** a supply chain problem into sub-problems so as to decompose a complex problem into a number of manageable and smaller problems, which will expedite the planning and scheduling. Although a trade-off between the speed of the optimization and the quality of the near optimal local solutions may exist, by using an

appropriate performance measure, it is possible to derive a near global optimal or ‘good-enough’ solution efficiently;

Note: The data in Global Manufacturing Materials Flow Network refers to the data in e-Business Information Flow Network.

↪ : Data directly from data source

⬆ : Manipulated data or data generated from other modules

Figure 6 - 1 System structure of supply chain virtual clustering (SCVC)

(2) Help to split a supply chain optimization problem purposefully instead of blindly so that

it can be executed on multiple distributed computers concurrently with less interference;
and

- (3) Use as a plug-in and can possibly be integrated with existing supply chain optimization systems.

6.3 Heuristic of an Evolutionary Approach to Fuzzy Clustering for SCVC

It is obvious from the discussion in Section 6.1 that c , the number of cluster centres, and m , the weighting exponent, have to be predetermined for the fuzzy c-means approach. This section focuses on supply chain virtual clustering as well as the enhancement of the MBEA enabled fuzzy c-means approach described in Section 4.3.5 to enable the determination of the best c and m for fuzzy clustering.

6.3.1 Problem Definition

The problem definition for Supply_Matrix using fuzzy c-means has been presented in Section 4.3.5.2. It is further summarized as follows.

Similarly, a typical $n \times p$ Supply_Matrix, which represents n work orders and p supply chain units, can be expressed using Equation 6-1. This forms the input data of a supply chain virtual clustering problem.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{p1} & x_{p2} & \dots & x_{pn} \end{bmatrix} = (x_{ij}) \quad (6-1)$$

where

p : Total number of supply chain units.

n : Total number of work orders.

$x_j = (x_{1j}, x_{2j}, \dots, x_{pj})$ is the j^{th} work order .

$$x_{lj} = \begin{cases} 1, & \text{if unit } l \text{ process order } j \\ 0, & \text{if unit } l \text{ doesn't process order } j \end{cases} \quad l = 1, 2, \dots, p; j = 1, 2, \dots, n$$

In fuzzy clustering, classification results can be expressed as a fuzzy cluster matrix as shown in Equation 6-2.

$$U = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{c1} & u_{c2} & \dots & u_{cn} \end{bmatrix} = (u_{ij}) \quad (6-2)$$

where

c : Number of cluster centre

u_{ij} : Degree of membership of work order j to cluster i

subject to:

$$0 \leq u_{ij} \leq 1, \quad i = 1, 2, \dots, c; j = 1, 2, \dots, n$$

$$\sum_{i=1}^c u_{ij} = 1, \quad j = 1, 2, \dots, n$$

$$0 < \sum_{j=1}^n u_{ij} \leq n, \quad i = 1, 2, \dots, c$$

The sum of the square error function which measures the dissimilarity between the data points and their cluster centre by the Euclidean distance is often used. It can be defined using Equation 6-3.

$$\min \{J_m(U, V) = \sum_{j=1}^n \sum_{i=1}^c (u_{ij})^m (d_{ij})^2\} \quad (6-3)$$

where

$$(d_{ij})^2 = |x_j - v_i|^2 = \sum_{l=1}^p (x_{jl} - v_{il})^2 \text{ is the Euclidean distance}$$

$$v_i = (v_{i1}, v_{i2}, \dots, v_{ip}) \text{ is the } i^{th} \text{ cluster centre}$$

$$v_{li} = \frac{\sum_{j=1}^n (u_{ij})^m x_{lj}}{\sum_{j=1}^n (u_{ij})^m} \quad (6-4)$$

$m \in [1, \infty]$ is the weighting exponent on each fuzzy membership. The larger the m is, the fuzzier the partition will be. Normally, the value of m is between 1.25 and 3.

6.3.2 MBEA Enabled Fuzzy C-Means Approach to SCVC

As shown in Figure 6-2, TS is embedded into the GA to implement the multiple population search strategy that is able to facilitate the search process, help determine the fuzzy c-means parameters and generate next generation of chromosomes, and avoid premature convergence. Basically, the aforementioned supply chain virtual clustering problem using fuzzy c-means is a minimization problem in nature which is to minimize the $J_m(U, V)$.

Figure 6 - 2 Flow chart of the proposed MBEA enable fuzzy c-means approach to supply chain virtual clustering (SCVC)

In a normal fuzzy c-means implementation, it usually takes a lot of trial-and-error attempts and comparisons using a validity index (Wang and Zhang 2007) to find proper fuzzy c-means parameters, c and m . As mentioned in Section 6.1, to overcome this weakness, the

MBEA enabled fuzzy c-means approach described in Chapter 4 is further enhanced to automatically identify optimal fuzzy c-means parameters. Thus, in each GA run, multiple populations with different fuzzy c-means parameters are used.

Figure 6 - 3 Flow chart of searching and updating FCM parameters for SCVC

As mentioned in Section 4.3.5, these populations are treated as ‘individuals’ in the tabu search and are concurrently reproduced by GA operators. At the end of each GA generation, the promise level for a parameter set can be computed by the equations outlined in Section 6.3.3. Subsequently, the best parameter set in terms of promise level is selected. From the tabu search point of view, the GA run is used to evaluate the objective function which depicts the promise level of the fuzzy c-means parameter set, while the number of populations of a GA is the number of individuals maintained in the tabu search. For example, for every five generations of GA runs, the promise level of each parameter set of the GA population is evaluated and used as the value attained by the objective function for the selection of the best fuzzy c-means parameter set. The neighbourhood parameter set is then created and used in

the succeeding GA runs. The procedures for searching and updating the fuzzy c-means parameter set and for the generation of neighbourhood parameter set are depicted in Figures 6-3 and 6-4, respectively. The promise level of a parameter set for a population can be derived using the formulae listed in Section 6.3.3.

Figure 6 - 4 Flow chart of neighbourhood creation for SCVC

As shown in Figure 6-4, in neighbourhood creation, the length of steps taken by c and m , namely s_c and s_m , are determined by the maximum ($s_c^{\max}, s_m^{\max}$) and minimal steps ($s_c^{\min}, s_m^{\min}$) of the c and m respectively.

6.3.3 FCM Validity Index and Promise Level Calculation

A new validity index has been proposed for the MBEA to compare the performance of different GA populations with different c and m by taking into consideration the inter-cluster transportation and group efficiency. It serves as the objective function to guide the TS. The proposed validity index V_{xf} that considers both inter-cluster transportation and group efficiency is given as follows.

$$V_{xf} = E + F / c \quad (6-5)$$

where

$$E = \frac{\sum_{j=1}^n \sum_{l=1}^p \sum_{s_j \neq t_l} x_{lj}}{\sum_{j=1}^n \sum_{l=1}^p x_{lj}} \quad (6-6)$$

$$F = \sum_{i=1}^c \frac{\sum_{s_j=i} \sum_{t_l=i} (1 - x_{lj})}{\sum_{s_j=i} \sum_{t_l=i} x_{lj} + \sum_{s_j=i} \sum_{t_l=i} (1 - x_{lj})} \quad (6-7)$$

s_j and t_l is the cluster centre the j^{th} work order and l^{th} supply chain unit belongs to respectively. They are given by the following formulae.

$$\begin{aligned} s_j &= i, \text{ if } u_{ij} = \max_{i=1}^c (u_{ij}), \quad j = 1, 2, 3, \dots, n \\ t_l &= i, \text{ if } v_{li} = \max_{i=1}^c (v_{li}), \quad l = 1, 2, 3, \dots, p \end{aligned} \quad (6-8)$$

The promise level is further computed from the V_{xf} .

$$P_{km} = w_{best} (V_{xf})_{km}^{best} + w_{avg} (V_{xf})_{km}^{avg} \quad (6-9)$$

where

$(V_{xf})_{km}^{best}$: *Validity index value of the best chromosome of m^{th} population of k^{th} generation.*

$(V_{xf})_{km}^{avg}$: *Average validity index value of chromosomes of m^{th} population of k^{th} generation.*

p_{km} : *Promise level of m^{th} population of k^{th} generation.*

w_{best} : *Weight of $(V_{xf})_{km}^{best}$.*

w_{avg} : *Weight of $(V_{xf})_{km}^{avg}$.*

The promise level determined using Equation 6-9 is then subjected to MBEA to compute the best combination of c and m .

6.3.4 Chromosome Representation, Fitness Evaluation and GA Operators

Using the Supply_Matrix converter, a Supply_Graph and related work orders are transformed into a Supply_Matrix. The chromosome representation, fitness function and GA operators described in Section 4.3.5 can be used to perform supply chain virtual clustering. The difference between the evolutionary approach to fuzzy c-means for supply chain virtual clustering and that depicted in Section 4.3.5 is that the MBEA in the SCVC module is to find the near optimal fuzzy c-means parameters, namely c and m , while the approach described in Section 4.3.5 is to search for the suitable compromised pair of GA parameters, namely the crossover probability, p_c , and the mutation probability, p_m .

6.3.5 Work Order and Supply Chain Unit Families Generation

As mentioned in Section 4.3.5.7, the final fuzzy cluster matrix U^* and the final cluster centre matrix V^* worked out by the MBEA enabled SCVC can be used to generate the final work order families and associated supply chain unit families.

As such, the supply chain unit-transportation-work order families can be organized by combining the supply chain unit and work order families achieved by the SCVC module with the preferred transportation modes associated with the relevant supply chain units and work

orders that are determined by the RSO module.

6.4 Examples and Discussions

Figure 6 - 5 Functional structure of the prototype SCVC

The functional structure of the SCVC module developed is shown in Figure 6-5. Similar to the RSO module, the SCVC module provides the following functions: *data input*, *system configuration*, *SCVC optimizer control* and *SCVC result output*. The necessary input data for this module such as Supply_Matrix can be extract from the RSO module or imported from data files through the *data input* function. The *system configuration* provides functions for user to configure the optimization engine, FCM, GA, TS, MBEA and define their related parameters and the constraints and objective functions that are required by the optimization engine. The users can control the running of the *SCVC optimizer* and monitor the status and the progress of the optimization engine through the *SCVC engine control* and the *runtime*

monitor. The *SCVC result output* function provides the optimal cluster centres, the result of virtual clusters and the statistic data obtained.

As mentioned in Section 6.2, the sub-module of SCVC, which is the Supply_Matrix Converter, is able to transform a Supply_Graph that represents the supply chain units and order routings into a Supply_Matrix. It can then be optimized by the MBEA enabled SCVC to form the supply chain unit-transportation-work order families. The examples described in this section begin with the Supply_Matrix for ease of explanation, as the Supply_Matrix Converter has already been discussed in Section 4.2.3. Once an optimal fuzzy cluster matrix has been generated by the MBEA enabled SCVC, the supply chain unit-transportation-work order families can be easily formed using the procedures described in Section 6.3.5.

Five sets of sample Supply_Matrix data are used to illustrate the capability of the proposed SCVC. Two 10x10 Supply_Matrices with respectively 3 and 5 cluster centres are used in Examples 1 and 2. Example 3 used the same data set of Example 1 but with the introduction of some irregularities. Examples 4 and 5 further illustrated the effectiveness of the proposed evolutionary approach through two matrices gleaned from literature. Both matrices contain some exceptional points that introduce complexity into the data set. Since the SCVC model adopts the virtual clustering which is a concept derived from the group technology, it is reasonable, to adapt the data sets (with known results) extracted from the literature on group technology and use them for the comparative study.

Throughout the five examples and simulation runs, it can be seen that the proposed hybrid evolutionary approach is able to find the best c and m while searching for the best supply chain families. This overcomes the necessity to pre-define suitable values for the parameters c and m of fuzzy c-means which may not be known as a prior knowledge.

6.4.1 Example 1: a 10x10 Supply_Matrix with 3 Cluster Centres

The 10x10 Supply_Matrix is given in Table 6-1. It is the same data set that was used in

Section 4.3.6.1 and has three cluster centres. To illustrate the capability of the proposed hybrid evolutionary approach, five pairs of columns or rows of the table were randomly selected and their positions were swapped. For example, columns *su1* and *su9*, and subsequently, rows *wo6* and *wo8* are swapped to form a ‘new’ table. After such an operation, the information registered in the ‘new’ table is used as inputs for the evaluation.

Table 6 - 1 Supply_Matrix 1

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>wo1</i>	1	1	1	0	0	0	0	0	0	0
<i>wo2</i>	1	1	1	0	0	0	0	0	0	0
<i>wo3</i>	1	1	1	0	0	0	0	0	0	0
<i>wo4</i>	0	0	0	1	1	1	0	0	0	0
<i>wo5</i>	0	0	0	1	1	1	0	0	0	0
<i>wo6</i>	0	0	0	1	1	1	0	0	0	0
<i>wo7</i>	0	0	0	0	0	0	1	1	1	1
<i>wo8</i>	0	0	0	0	0	0	1	1	1	1
<i>wo9</i>	0	0	0	0	0	0	1	1	1	1
<i>wo10</i>	0	0	0	0	0	0	1	1	1	1

Note: *wo_i* and *su_i* denote work orders and supply chain units respectively

Table 6 - 2 Parameters used in simulation run

Parameters	Value	Description
Number_of_generation_for_parameter_updating	20	Number of GA generations between two consecutive TS for parameter updating
FC_c_Min	3	Minimal number of cluster of fuzzy c-means
FC_c_Max	10	Maximal number of cluster of fuzzy c-means
FC_c_Step_Min	1	Minimal step for neighbourhood search of parameter <i>c</i>
FC_c_Step_Max	2	Maximal step for neighbourhood search of parameter <i>c</i>
FC_m_Min	1.25	Minimal number of <i>m</i> of fuzzy c-means
FC_m_Max	3	Maximal number of <i>m</i> of fuzzy c-means
FC_m_Step_Min	0.01	Minimal step for neighbourhood search of parameter <i>m</i>
FC_m_Step_Max	0.3	Maximal step for neighbourhood search of parameter <i>m</i>
GA_number_of_generation	200	Total number of GA generations
GA_population_size	100	GA population size
GA_crossover_rate	0.9	GA crossover probability
GA_mutation_rate	0.1	GA mutation probability
GA_elitist_rate	0.08	Percentage for GA elitist strategy
TS_number_of_individual	4	Number of GA populations for TS
TS_new_population_elitist_rate	0.2	Percentage of the best chromosome to be selected into the new population after TS parameter updating
TS_length_of_tabu_list	8	Tabu list length
TS_promise_level_weightage (best/average)	1/0	The weightages for best and average promise level respectively

Table 6-2 lists the parameters used in the computation of fuzzy c-means, GA and TS. Figure 6-6 depicts the mean value of 10 simulation runs of the number of cluster centre in each updating of parameters. The hybrid approach can quickly reach the optimal number of cluster in around five to six updating of parameters, i.e. iterations. A typical final fuzzy cluster matrix U^* and cluster centre matrix V^* are summarized in Table 6-3. Obviously, the optimal cluster allocation shown in Table 6-1 can be reached.

Figure 6 - 6 The best number of cluster centre of MBEA for Example 1

Table 6 - 3 The fuzzy cluster matrix U^* and cluster centres V^* for Example 1

U^*										
	<i>wo1</i>	<i>wo2</i>	<i>wo3</i>	<i>wo4</i>	<i>wo5</i>	<i>wo6</i>	<i>wo7</i>	<i>wo8</i>	<i>wo9</i>	<i>wo10</i>
<i>c1</i>	0.00	0.00	0.00	0.01	0.00	0.00	0.78	0.73	0.57	0.74
<i>c2</i>	0.80	0.79	0.81	0.02	0.00	0.02	0.08	0.11	0.20	0.15
<i>c3</i>	0.20	0.21	0.19	0.97	1.00	0.98	0.14	0.16	0.23	0.11

V^*										
	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>c1</i>	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
<i>c2</i>	0.99	0.99	0.99	0.00	0.00	0.00	0.01	0.01	0.01	0.01
<i>c3</i>	0.01	0.01	0.01	0.98	0.98	0.98	0.01	0.01	0.01	0.01

Note: wo_i , su_i and c_i denote work orders, supply chain units and cluster centres respectively

The highlighted numbers in Table 6-3 show the maximum degree of membership of each work order as well as the best-fit cluster for a particular work order. For example, *wo1* belongs to Cluster 2 (U^*) as it has the highest membership value 0.8.

6.4.2 Example 2: a 10x10 Supply_Matrix with 5 Cluster Centres

Another 10x10 Supply_Matrix is given in Table 6-4 which consists of five clusters. Similar

to Example 1, five pairs of columns or rows of the table were randomly chosen to undergo the swapping operation.

Table 6 - 4 Supply_Matrix 2

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>wo1</i>	1	1	0	0	0	0	0	0	0	0
<i>wo2</i>	1	1	0	0	0	0	0	0	0	0
<i>wo3</i>	0	0	1	1	0	0	0	0	0	0
<i>wo4</i>	0	0	1	1	0	0	0	0	0	0
<i>wo5</i>	0	0	0	0	1	1	0	0	0	0
<i>wo6</i>	0	0	0	0	1	1	0	0	0	0
<i>wo7</i>	0	0	0	0	0	0	1	1	0	0
<i>wo8</i>	0	0	0	0	0	0	1	1	0	0
<i>wo9</i>	0	0	0	0	0	0	0	0	1	1
<i>wo10</i>	0	0	0	0	0	0	0	0	1	1

Note: wo_i and su_i denote work orders and supply chain units respectively

Figure 6 - 7 the best number of cluster centre of MBEA for Example 2

Table 6 - 5 The fuzzy cluster matrix U^* and cluster centres V^* for Example 2

U^*										
	<i>wo1</i>	<i>wo2</i>	<i>wo3</i>	<i>wo4</i>	<i>wo5</i>	<i>wo6</i>	<i>wo7</i>	<i>wo8</i>	<i>wo9</i>	<i>wo10</i>
<i>c1</i>	0.173	0.154	0.202	0.209	0.187	0.208	0.222	0.220	0.198	0.199
<i>c2</i>	0.181	0.184	0.228	0.222	0.204	0.208	0.189	0.186	0.202	0.208
<i>c3</i>	0.199	0.206	0.184	0.185	0.207	0.189	0.198	0.204	0.219	0.219
<i>c4</i>	0.260	0.265	0.181	0.184	0.177	0.165	0.182	0.179	0.190	0.198
<i>c5</i>	0.188	0.190	0.205	0.200	0.224	0.230	0.209	0.211	0.191	0.186

V^*										
	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>c1</i>	0.134	0.134	0.216	0.216	0.199	0.199	0.250	0.250	0.201	0.201
<i>c2</i>	0.162	0.162	0.251	0.251	0.209	0.209	0.171	0.171	0.207	0.207
<i>c3</i>	0.205	0.205	0.168	0.168	0.196	0.196	0.202	0.202	0.229	0.229
<i>c4</i>	0.347	0.347	0.163	0.163	0.143	0.143	0.160	0.160	0.186	0.186
<i>c5</i>	0.170	0.170	0.197	0.197	0.250	0.250	0.213	0.213	0.170	0.170

Note: wo_i , su_i and c_i denote work orders, supply chain units and cluster centres respectively

The parameters used in this example are the same as the parameters in Example 1 except for the generation of GA is 400 instead of 200. Figure 6-7 depicts the mean value of 10 simulation runs of the number of cluster centre in each parameter updating. An optimal number of cluster centres of five can be obtained after 12 iterations. A typical final fuzzy cluster matrix U^* and cluster centre matrix V^* is described in Table 6-5. It is obviously that the optimal cluster allocation shown in Table 6-4 can be reached.

6.4.3 Example 3: a 10x10 Supply_Matrix with Noise

The 10x10 Supply_Matrix with noise being introduced is given in Table 6-6. It is the same matrix used in Example 1 with irregularities such as cells $wo2su7$ and $wo7su3$. Similar to Examples 1 and 2, five pairs of columns or rows of the table were randomly picked to undergo the swapping operation.

Table 6 - 6 Supply_Matrix 3

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>wo1</i>	1	1	1	0	0	0	0	0	0	0
<i>wo2</i>	1	1	1	0	0	0	1	0	0	0
<i>wo3</i>	1	1	1	0	0	0	0	0	0	0
<i>wo4</i>	0	0	0	1	1	1	0	0	0	0
<i>wo5</i>	0	0	0	1	1	1	0	0	0	0
<i>wo6</i>	0	0	0	1	1	1	0	0	0	0
<i>wo7</i>	0	0	1	0	0	0	1	1	1	1
<i>wo8</i>	0	0	0	0	0	0	1	1	1	1
<i>wo9</i>	0	0	0	0	0	0	1	1	1	1
<i>wo10</i>	0	0	0	0	0	0	1	1	1	1

Note: wo_i and su_i denote work orders and supply chain units respectively

The parameters used in this simulation run are the same as those reported in Example 1. The irregularities introduced did not cause any trouble for the hybrid approach to obtain the optimal results. Figure 6-8 depicts the mean value of 10 simulation runs of the number of cluster centre in each iteration. It exhibits the similar trend and the hybrid approach can quickly determine the optimal number of cluster in five to six updating of parameters. A typical final fuzzy cluster matrix U^* and a final cluster centre matrix V^* are depicted in Table 6-7. It is apparent that the optimal cluster allocation shown in Table 6-6 can be obtained.

Figure 6 - 8 The best number of cluster centre of MBEA for Example 3

Table 6 - 7 The fuzzy cluster matrix U^* and cluster centres V^* for Example 3

U^*										
	<i>wo1</i>	<i>wo2</i>	<i>wo3</i>	<i>wo4</i>	<i>wo5</i>	<i>wo6</i>	<i>wo7</i>	<i>wo8</i>	<i>wo9</i>	<i>wo10</i>
<i>c1</i>	0.843	0.579	0.553	0.002	0.015	0.027	0.256	0.181	0.131	0.217
<i>c2</i>	0.118	0.169	0.236	0.832	0.896	0.807	0.166	0.038	0.001	0.132
<i>c3</i>	0.039	0.252	0.211	0.166	0.090	0.166	0.578	0.781	0.869	0.651

V^*										
	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>
<i>c1</i>	0.965	0.965	0.982	0.000	0.000	0.000	0.230	0.035	0.035	0.035
<i>c2</i>	0.011	0.011	0.013	0.986	0.986	0.986	0.006	0.004	0.004	0.004
<i>c3</i>	0.016	0.016	0.134	0.006	0.006	0.006	0.988	0.978	0.978	0.978

Note: wo_i , su_i and c_i denote work orders, supply chain units and cluster centres respectively

6.4.4 Example 4: a 9x9 Matrix Data Set

In this sub-section, the hybrid approach was used to evaluate a typical 9x9 matrix (Table 6-8) from the work of Chu and Hayya (1991).

Table 6 - 8 Matrix data set 4

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>
<i>wo1</i>	1	1	0	0	1	0	0	0	0
<i>wo2</i>	1	1	0	0	0	1	0	0	1
<i>wo3</i>	0	0	1	0	0	0	1	1	0
<i>wo4</i>	0	1	1	1	0	0	0	1	0
<i>wo5</i>	1	0	0	1	1	0	0	1	0
<i>wo6</i>	0	1	0	0	0	1	0	0	1
<i>wo7</i>	0	0	1	0	0	0	1	1	0
<i>wo8</i>	0	0	1	1	1	0	1	1	0
<i>wo9</i>	0	1	0	0	0	1	0	0	1

Note: wo_i and su_i denote work orders and supply chain units respectively

Figure 6 - 9 the best number of cluster centre of MBEA of Example 4

Table 6 - 9 The fuzzy cluster matrix U^* and cluster centres V^* for Example 4

U^*									
	<i>wo1</i>	<i>wo2</i>	<i>wo3</i>	<i>wo4</i>	<i>wo5</i>	<i>wo6</i>	<i>wo7</i>	<i>wo8</i>	<i>wo9</i>
<i>c1</i>	0.692	0.005	0.013	0.265	0.606	0.255	0.064	0.257	0.217
<i>c2</i>	0.105	0.058	0.919	0.589	0.322	0.000	0.823	0.656	0.052
<i>c3</i>	0.202	0.936	0.068	0.145	0.072	0.745	0.113	0.087	0.730

V^*									
	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>
<i>c1</i>	0.612	0.605	0.215	0.476	0.707	0.174	0.115	0.495	0.174
<i>c2</i>	0.105	0.200	0.887	0.429	0.284	0.017	0.723	0.964	0.017
<i>c3</i>	0.405	0.932	0.088	0.065	0.082	0.848	0.055	0.102	0.848

Note: wo_i , su_i and c_i denote work orders, supply chain units and cluster centres respectively

Table 6 - 10 Optimized Supply_Matrix for Example 4

	<i>su1</i>	<i>su4</i>	<i>su5</i>	<i>su3</i>	<i>su7</i>	<i>su8</i>	<i>su2</i>	<i>su6</i>	<i>su9</i>
<i>wo1</i>	1	0	1	0	0	0	1	0	0
<i>wo5</i>	1	1	1	0	0	1	0	0	0
<i>wo3</i>	0	0	0	1	1	1	0	0	0
<i>wo4</i>	0	1	0	1	0	1	1	0	0
<i>wo7</i>	0	0	0	1	1	1	0	0	0
<i>wo8</i>	0	1	1	1	1	1	0	0	0
<i>wo2</i>	1	0	0	0	0	0	1	1	1
<i>wo6</i>	0	0	0	0	0	0	1	1	1
<i>wo9</i>	0	0	0	0	0	0	1	1	1

Note: wo_i and su_i denote work orders and supply chain units respectively

The parameters used in this example are the same as those in Example 1 except for the followings.

- maximum $c = 6$;
- number of generation for parameter updating = 15; and

- maximum GA number of generation = 300.

Figure 6-9 depicts the mean value of the number of cluster centre against the updating of parameters in 10 simulation runs. It shows that the hybrid approach can quickly reach the optimal number of cluster in 13 parameter updating. A typical final fuzzy cluster matrix U^* and a cluster centre matrix V^* are depicted in Table 6-9. The final result of the clustering is shown in Table 6-10.

6.4.5 Example 5: a 19x11 Matrix Data Set

The hybrid approach was then used to evaluate a 19x11 matrix (Table 6-11) which was extracted from the work of Bedworth *et al.* (1991). Basically, it is the same data set that was described in Section 4.3.6.2.

Table 6 - 11 Matrix data set 5

	<i>su1</i>	<i>su2</i>	<i>su3</i>	<i>su4</i>	<i>su5</i>	<i>su6</i>	<i>su7</i>	<i>su8</i>	<i>su9</i>	<i>su10</i>	<i>su11</i>
<i>wo1</i>	0	1	0	1	0	1	0	0	0	0	0
<i>wo2</i>	1	0	0	1	0	1	0	1	0	0	0
<i>wo3</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo4</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo5</i>	0	0	0	0	0	0	1	0	0	1	1
<i>wo6</i>	0	0	0	1	1	0	0	0	1	0	0
<i>wo7</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo8</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo9</i>	0	0	1	1	0	0	0	0	0	0	0
<i>wo10</i>	0	1	0	1	0	1	0	1	0	0	0
<i>wo11</i>	1	0	0	1	0	1	0	1	0	0	0
<i>wo12</i>	0	0	0	1	1	0	1	0	1	0	0
<i>wo13</i>	0	0	0	0	0	0	1	0	0	1	1
<i>wo14</i>	0	0	1	1	0	0	0	0	1	0	0
<i>wo15</i>	0	0	0	1	0	0	0	0	0	0	0
<i>wo16</i>	0	1	0	0	0	0	0	0	0	0	0
<i>wo17</i>	0	0	0	0	0	0	1	0	0	0	0
<i>wo18</i>	0	0	0	1	0	0	0	1	0	0	0
<i>wo19</i>	0	0	0	1	0	0	1	0	0	0	0

Note: wo_i and su_i denote work orders and supply chain units respectively

The parameters used in this example are the same as those used in Example 1 except for

- maximum $c = 6$;
- GA population size = 200; and
- maximum number of generation = 400.

Figure 6-10 depicts the mean value of the number of cluster centre against updating of parameters in 10 simulations. It shows that even for a complex problem, the hybrid approach is able to derive the optimal number of cluster without much difficulty. A typical final fuzzy cluster matrix U^* and a cluster centre matrix V^* are presented in Table 6-12. The final result of the clustering is shown in Table 6-13.

Figure 6 - 10 The best number of cluster centre of MBEA for Example 5

Table 6 - 12 the fuzzy cluster matrix U^* and cluster centres V^* for Example 5

U^*											
	$wo1$	$wo2$	$wo3$	$wo4$	$wo5$	$wo6$	$wo7$	$wo8$	$wo9$	$wo10$	$wo11$
$c1$	0.324	0.321	0.277	0.257	0.362	0.326	0.227	0.249	0.254	0.324	0.311
$c2$	0.318	0.322	0.432	0.420	0.305	0.346	0.439	0.431	0.428	0.319	0.326
$c3$	0.358	0.357	0.291	0.323	0.333	0.328	0.334	0.320	0.318	0.357	0.363
	$wo12$	$wo13$	$wo14$	$wo15$	$wo16$	$wo17$	$wo18$	$wo19$			
$c1$	0.348	0.381	0.298	0.315	0.337	0.382	0.303	0.361			
$c2$	0.327	0.304	0.378	0.327	0.322	0.286	0.318	0.297			
$c3$	0.325	0.315	0.324	0.358	0.341	0.332	0.379	0.342			
V^*											
	$su1$	$su2$	$su3$	$su4$	$su5$	$su6$	$su7$	$su8$	$su9$	$su10$	$su11$
$c1$	0.102	0.172	0.175	0.682	0.124	0.212	0.400	0.202	0.229	0.166	0.166
$c2$	0.079	0.113	0.521	0.869	0.088	0.153	0.162	0.153	0.328	0.065	0.065
$c3$	0.127	0.179	0.265	0.803	0.095	0.252	0.244	0.263	0.221	0.093	0.093

Note: wo_i , su_i and c_i denote work orders, supply chain units and cluster centres respectively

Throughout the five examples and simulation runs, it can be seen that the optimal cluster allocation can be obtained by the proposed MBEA enabled SCVC. Simultaneously, the

hybrid approach is able to find the optimal number of cluster.

Table 6 - 13 Optimized Supply_Matrix for Example 5

	<i>su5</i>	<i>su7</i>	<i>su10</i>	<i>su11</i>	<i>su3</i>	<i>su4</i>	<i>su9</i>	<i>su1</i>	<i>su2</i>	<i>su6</i>	<i>su8</i>
<i>wo5</i>	0	1	1	1	0	0	0	0	0	0	0
<i>wo12</i>	1	1	0	0	0	1	1	0	0	0	0
<i>wo13</i>	0	1	1	1	0	0	0	0	0	0	0
<i>wo17</i>	0	1	0	0	0	0	0	0	0	0	0
<i>wo19</i>	0	1	0	0	0	1	0	0	0	0	0
<i>wo3</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo4</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo6</i>	1	0	0	0	0	1	1	0	0	0	0
<i>wo7</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo8</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo9</i>	0	0	0	0	1	1	0	0	0	0	0
<i>wo14</i>	0	0	0	0	1	1	1	0	0	0	0
<i>wo1</i>	0	0	0	0	0	1	0	0	1	1	0
<i>wo2</i>	0	0	0	0	0	1	0	1	0	1	1
<i>wo10</i>	0	0	0	0	0	1	0	0	1	1	1
<i>wo11</i>	0	0	0	0	0	1	0	1	0	1	1
<i>wo15</i>	0	0	0	0	0	1	0	0	0	0	0
<i>wo16</i>	0	0	0	0	0	0	0	0	1	0	0
<i>wo18</i>	0	0	0	0	0	1	0	0	0	0	1

Note: wo_i and su_i denote work orders and supply chain units respectively

6.5 Summary

This chapter presents the detailed design of the SCVC module which consists of four key sub-modules, namely Supply_Matrix Converter, Performance Measure, SCVC Optimization Engine, and SCVC Output.

In order to effectively organize the supply chain units, transportation modes and work orders into different unit-transportation-work order families, the SCVC module adopts the MBEA enabled fuzzy c-means approach described in Section 4.3.5 and equips it with the ability to search for the optimal clustering parameters, c and m . In so doing, the MBEA enabled SCVC eliminates the necessity to pre-define the suitable value of c and m for fuzzy c-means.

Furthermore, a new fuzzy c-means validity index that combines the inter-cluster transportation and group efficiency is created to help the calculation of the promise level that serves as the objective function to determine how good a set of clustering parameter is.

Finally, the capability and effectiveness of the proposed MBEA enabled SCVC is illustrated using five examples. The results show that it is able to find the optimal fuzzy c-means parameters in all the five examples. The optimal fuzzy cluster matrix can also be obtained by the proposed hybrid approach without difficulty.

Chapter 7 AN INTELLIGENT AGENT-BASED DISTRIBUTED ARCHITECTURE FOR SUPPLY CHAIN ORDER SCHEDULING

7.1 Introduction

As mentioned in Chapter 6, a complex supply chain optimization problem can be virtually and dynamically organized by the SCVC module into some supply chain unit-transportation-work order families (supply chain clusters) to facilitate the supply chain order scheduling. Subsequently, work orders are processed and optimized within the respective families as much as possible. The SCOS module is tasked to coordinate the schedules and local decisions worked out by each individual supply chain cluster as the optimal schedule for an individual cluster may be in conflict with the requirements of other clusters. In order to efficiently resolve the conflicts as well as to generate a near optimal schedule for the entire supply chain, software agents are used by the SCOS module as they possess the ability to

- delegate tasks;
- negotiate and communicate with other software agents within the system; and
- find a feasible and near-optimal solution to the entire supply chain intelligently by adapting themselves to changing environments.

This chapter describes the third module of SCASO, the SCOS module, which leverages on an intelligent agent-based distributed architecture (Yin *et al.* 2010). A GA-enhanced dynamic scheduler for multiple supply chain clusters developed by Khoo *et al.* (2000) and Yin (2000) is adapted and enhanced to realize the SCOS module, which is the core scheduling engine.

7.2 Overview of Software Agents

In the artificial intelligence community, numerous research groups in universities and research laboratories are building what have come to be called software agents. Software agents work by allowing people to delegate work that they could have done, to the agent software. Agents can automate repetitive tasks, intelligently summarise complex data; learn from other agents; negotiate with other agents to accomplish certain purposes; and even make recommendations (Ahmad *et al.* 2008, Bradshaw 1997).

Software agents are kinds of computer programs that interact with software environment such as operating system, Internet sites, information databases, other agents, and so forth, in order to achieve certain goals (Ahmad *et al.* 2008). They are one of the fastest growing research areas of information technology. In recent years, agent technology has been applied to many fields, such as information retrieval (Htoon and Thet 2008, Siddiqui and Tiwary 2005), distributed meeting scheduling (Glezer 2003, Shakshuki *et al.* 2008), manufacturing control and design (Han and Jafari 2003, Lastra and Colombo 2006, Zhang and Xie 2007) and many others.

Software agents are different from other applications by their additional attributes (Ahmad *et al.* 2008, Brenner *et al.* 1998). They are:

- (1) Software agents are autonomous and intelligent; they are able to solve tasks without the intervention of users. All agents have control over their own actions and are goal-driven, which means agents have a purpose and act in accordance with that purpose;
- (2) Software agents have social ability. They interact, communicate or negotiate with other software agents in order to complete their problem solving or cooperate with each other;
- (3) Software agents are reactive. That is, an agent senses changes in its world and responds in a designed pattern. All agents continue to run even when the user is gone, in order to achieve the purpose of the user;
- (4) Software agents are robust. They are autonomous and presumably doing something

important, agents must be able to respond unexpected changes and recover from errors in their computation world;

- (5) Software agents are adaptive. They can modify their behaviours over time in response to changing environments or an increase in knowledge about their problem solving;
- (6) Software agents are typically distributed across a network; and
- (7) Some agents are mobile, and move from machine to machine in order to enhance the ability of problem solving.

The above attributes of software agents show that they can simplify the complexities of distributed problems and coordinate with each other to solve the problems in a more natural, more efficient and more effective way.

7.3 Overview of the Intelligent Agent-Based Distributed Architecture for SCOS

The proposed intelligent agent-based distributed architecture for the SCOS module consists of two subsystems, the Supply Chain Scheduling Master (SCSM) and Supply Chain Scheduling Client (SCSC). Figures 7-1 and 7-2 depict the overall system structure and the architecture of the SCOS module respectively.

The SCSM maintains all the necessary information in the scheduling database for the scheduling of the entire supply chain. At the same time, it provides a negotiation locale for the supply chain cluster negotiators, which are the representatives of the supply chain cluster agents (SCCA), to resolve their conflicts with the aid of a decision-making module under the supervision of a supply chain supervisory agent (SCSA). The SCSC, on the other hand, retrieves all the scheduling information and knowledge related to the various supply chain clusters from the SCSM. Each supply chain unit-transportation-work order family that is worked out by the SCVC module is represented by a supply chain scheduling client (SCSC). It is used to determine the local near optimal schedule for every supply chain cluster. It also co-ordinates the activation of supply chain cluster agents and their negotiators, and controls

the communication among the SCSA and SCCAs, so as to derive the feasible or the near optimal schedule for the entire supply chain according to the objectives and decision-making policies.

Note: The data in Global Manufacturing Materials Flow Network refers to the data in e-Business Information Flow Network.

➤ : Data directly from data source

⬆ : Manipulated data or data generated from other modules

Figure 7 - 1 System structure of supply chain order scheduler (SCOS)

Figure 7 - 2 Overall architecture of the SCOS

7.4 Agents Involved in the SCOS

As mentioned, there are two types of software agents used in this work. They are the supply chain supervisory agent (SCSA) and supply chain cluster agents (SCCAs).

7.4.1 Supply Chain Supervisory Agent (SCSA)

The supervisory agent (Figure 7-3), which always maintains a list of all the supply chain clusters and keeps track of all the activated supply chain cluster agents in the system, is the *de facto* manager of all the software agents. It has four sub-modules namely a supervisor, a communicator, a decision maker and a data format interpreter. The supervisor is tasked to co-ordinate the activities of the various modules of the supervisory agent. It monitors the status of the supply chain cluster agents and receives the results (bid data) worked out by them. These bid data are then forwarded to the decision maker for negotiation and decision making. The communicator is the I/O of the SCSA. It enables and establishes the communication

among the supervisory agent, supply chain cluster negotiators and supply chain cluster agents. The decision maker, which is essentially a knowledge-based system (KBS), is controlled by the supervisor. Upon activation, it prioritises the supply chain cluster negotiators based on the rules or decision-making policies residing in the domain knowledge base, relevant scheduling information gleaned from the scheduling database and the bespoke bid data. Details of the supply chain cluster negotiators are presented in Section 7.4.2. Basically, the decision-making module carries out the following tasks.

Figure 7 - 3 Structure of supply chain supervisory agent (SCSA)

- (1) Retrieve all the schedules determined at supply chain cluster level;
- (2) Perform a pair-wise comparison using the schedules retrieved in Step 1 to check for conflicts;
- (3) Resolve the conflicts using the rules from the domain knowledge base and the bid data offered by the supply chain cluster negotiators to prioritise the supply chain clusters;
- (4) Instruct affected supply chain clusters to reschedule via the communicator; and
- (5) Repeat the above until a conflict-free schedule for the entire manufacturing system has been established.

The rules of the KBS are presented in Section 7.5.2. In Step 4, once a re-schedule instruction

is sent to the affected supply chain clusters, the work order scheduling engine of the SCSC works out another local optimal schedule under a set of new constraints such as the new starting time of work orders that may need to travel to other supply chain clusters.

The data format interpreter is used to translate the information from the supply chain cluster agents into the information that the SCSM and the SCSA can understand and use. It serves as some kind of communication protocol that helps the SCSM/SCSA understand the data sent over from the SCSC/SCCA.

7.4.2 Supply Chain Cluster Agent (SCCA).

Figure 7 - 4 Structure of a supply chain cluster agent (SCCA)

Basically, a supply chain cluster agent (Figure 7-4) is packaged with the scheduling information and the domain knowledge of a particular supply chain cluster. A supply chain cluster agent comprises five sub-modules, namely a communicator, a data format interpreter, a supply chain cluster agent controller, and a bid evaluator. The communicator, which is the I/O of the supply chain cluster agent, takes care of the data communication activities between the supply chain supervisory agent residing in the SCSM and other supply chain cluster agents. Similar to the supply chain supervisory agent, it also possesses a data format interpreter to translate the data received from the SCSM. The supply chain cluster controller

oversees the operations of all the modules in a supply chain cluster agent, such as communication, and scheduling and rescheduling instructions to work order scheduling engine. Once the scheduling engine has completed scheduling the tasks on a supply chain cluster, the bid evaluator is instantiated by the supply chain cluster controller to derive a set of bid data using the schedule computed for the supply chain cluster. The bid data consists of different scheduling attributes, such as the number of work order in the supply chain cluster, the processing start/end time of work orders, the due date of work orders and so on. These data and the supply chain cluster schedule are then forwarded to the representative of the supply chain cluster that is the supply chain cluster negotiator, and the scheduling database (both residing in the SCSM) respectively (Figure 7-2). The reason for residing the supply chain cluster negotiator instead of the whole supply chain cluster agent in the SCSM is to ease the scheduling load imposed on the SCSM. Using the supply chain cluster negotiators, instead of dealing directly with all the supply chain cluster agents, the SCSM only needs to provide a locale for negotiation and decision-making. This enables a complex supply chain scheduling problem to be decomposed into sub-tasks, which are handled at supply chain cluster level using local computers. An intelligent agent-based distributed architecture for scheduling multiple supply chain clusters is thus established. Once a supply chain cluster negotiator has received a rescheduling instruction from the decision maker of the SCSM, it will then instruct the supply chain cluster concerned to carry out the rescheduling task using the set of new constraints established in the decision making process mentioned in Section 7.4.1.

7.5 Structure of the Supply Chain Scheduling Master (SCSM)

The SCSM makes use of the scheduling database and the knowledge base to provide services to the scheduling system and supply chain cluster agents. The scheduling database is the repository of all the data necessary for scheduling, including the latest supply chain unit-

transportation-work order families, current supply chain cluster schedules, capacity and/or manufacturing processes of supply chain unit, work orders, process routings, materials, and scheduling parameters. The knowledge base contains the domain knowledge to support the intelligent decision-making activities of software agents. The knowledge is represented by decision rules that determine the priority of supply chain cluster negotiators and communication. It also contains the decision rules for conflict resolution.

Figure 7 - 5 Structure of supply chain scheduling master (SCSM)

Besides the scheduling database and the domain knowledge base, the SCSM system comes with a system configurator, a production rule editor, a system output generator and an agents' locale provider. The structure of SCSM is shown in Figure 7-5.

7.5.1 System Configurator

The system configurator provides the following functionalities:

- (1) Supervisory agent configuration. It allows the users to define decision-making policies and supply chain cluster scheduling attributes (Section 7.5.2) for decision-making.
- (2) Network setting. It defines the network properties, such as the IP address and the socket

port for communication.

- (3) Supply chain cluster configuration. It provides the users the means to modify the supply chain cluster, and define the constraints, objectives and scheduling parameters.

7.5.2 Knowledge-based System and Production Rule Editor

In this work, a KBS is used to prioritise supply chain cluster negotiators and resolves deadlocks or conflicting supply chain cluster schedules. The production rule editor is to enable the user for inputting, retrieving and modifying production rules.

An expert system shell, Jess, which includes the rule engine and the scripting environment written by Friedman-Hill (<http://www.jessrules.com>), is adopted for the development of the KBS for the SCOS module. Basically, Jess supports the development of rule-based KBSs that can be tightly coupled to codes written in the powerful, portable Java language. Basically, Jess is a productive development and delivery expert system shell and provides a complete environment for the construction of rule and/or object-based KBSs. It is said to have many thousands of users worldwide (<http://www.jessrules.com/links>).

Basically, the supply chain cluster with a higher priority will try to resolve the conflicts between itself and other supply chain cluster schedules and impose constraints on other supply chain clusters before their local schedules are rescheduled.

There are three sets of decision rules namely the rule set based on predefined priority of the supply chain cluster, the rule set based on scheduling attributes of supply chain clusters and the rule set based on the weighted scheduling attributes of supply chain clusters. It also has a rule set for deadlock resolution.

- ***Rule Set Based on Predefined Priority of the Supply Chain Cluster***

This set of rules is used to prioritise supply chain cluster negotiators simply based on the predefined priority of supply chain clusters that may reflect the relative importance of different supply chain clusters, the bottleneck and other practices of the supply chain. The

main rule of this rule set in pseudo-English form is as follows.

Rule #1

If (using predetermined supply chain cluster priorities)

And (predetermined supply chain cluster sequence for supply chain clusters in hand exists)

Then (return the supply chain cluster ID with higher supply chain cluster priority).

• ***Rule Set Based on Scheduling Attributes of Supply Chain Clusters***

There are many supply chain cluster scheduling attributes, which can be selected as the criteria to prioritise supply chain cluster negotiators. In this work, these scheduling attributes include:

- (1) Average work order priority;
- (2) Highest work order priority;
- (3) Number of work order;
- (4) Number of work order with deadline constraints;
- (5) Number of work order with start time constraints;
- (6) Percentage of work order with deadline constraints;
- (7) Percentage of work order with start time constraints; and
- (8) Priority of supply chain cluster.

Based on the priority or relative importance of scheduling attributes, Jess proceeds to define the priority of supply chain cluster negotiators.

For example, scheduling attributes such as average work order priority, number of work orders and the highest work order priority are considered. If the corresponding values of the three scheduling attributes of supply chain clusters 1 and 2 are 10, 20 and 30, and 10, 30 and 10 respectively, cluster 2 will be assigned a higher priority. The reason being, although it has the same average work order priority as cluster 1 (the first attribute), it has 10 more work orders than cluster 1 (the second attribute). The third attribute is then ignored. The main rules in pseudo-English form are listed below.

*Rule #1**If (using the priority of supply chain cluster scheduling attributes)**And (the value of the first attribute in the sequence of the first supply chain cluster is greater than that of the second supply chain cluster)**Then (return the supply chain cluster ID of the first supply chain cluster).**Rule #2**If (using the priority of supply chain cluster scheduling attributes)**And (the value of the first attribute in the sequence of the first supply chain cluster equals that of the second supply chain cluster)**And (...)**And (the value of the nth attribute in the sequence of the first supply chain cluster is greater than that of the second supply chain cluster)**Then (return the supply chain cluster ID of the first supply chain cluster)*

.

• Rule Set Based on the Weighted Scheduling Attributes of Supply Chain Clusters

Apart from having a value, each scheduling attribute is also assigned a weightage to reflect its relative importance. The final value for a supply chain cluster is that of the attribute and its weightage. The larger the final value of a supply chain cluster, the higher its priority. The supply chain cluster with a higher priority will impose constraints on other supply chain clusters when all supply chain cluster negotiators try to derive the global schedule. The schedule of the supply chain cluster with higher priority remains unchanged. The main rules in pseudo-English form are as follows.

*Rule #1**If (using the weights of supply chain cluster scheduling attributes)**Then (final value = (attribute 1 × weight 1 + ... + attribute n × weight n) / (attribute 1 + ... + attribute n)).**Rule #2**If (using the weights of supply chain cluster scheduling attributes)**And (final values of the supply chain clusters exist)**Then (return the supply chain cluster ID with largest final value).*

- ***Rule Set for Deadlock Resolution***

As already mentioned, the priority of a supply chain cluster is based on the final values computed. During each cycle of computation, the SCOS module actually carries out the following iterative tasks:

- Local scheduling by the dynamic schedulers of SCSC;
- Determining a near optimal schedule and/or detecting conflicts by SCSM; and
- Rescheduling of affected supply chain cluster if conflicts are detected.

Under certain circumstances that the values of all the attributes involved in decision-making are the same or similar to those of the previous cycle of computation, Jess may work out the same priority for supply chain cluster negotiators. This may cause some schedules that are feasible for individual supply chain clusters but unfeasible for the entire manufacturing system to be always accepted. As a result, deadlocks may occur. An easy and simple way for deadlock resolution is proposed and implemented in this work to monitor and break possible deadlock during program execution. The procedure is outlined as follows:

- (1) predefine the maximum number of iteration for rescheduling;
- (2) Check the iteration number every time when rescheduling is instantiated;
- (3) Carry out rescheduling if the iteration number is less than the predefined number;
- (4) Otherwise, reset the iteration number to zero and randomly select a supply chain cluster for rescheduling which is fairly similar to the mutation operation in GAs.

The above procedure temporarily suspends using the priority worked out for each of the supply chain cluster negotiators to derive the near optimal schedule for the entire manufacturing system. It randomly selects a supply chain cluster for rescheduling. As a result, the supply chain cluster schedule that causes a deadlock may be rejected. A new schedule can then be worked out. Such an action may eventually enable a compromised solution to be discovered.

For example, in cycle n , the priorities of the supply chain cluster negotiators is cluster 1 - one, cluster 3 - two and cluster 2 - three, which means cluster 1 will impose some constraints on cluster 2 and cluster 3 when they try to resolve the conflicts between them. Clusters 2 and 3 are rescheduled while cluster 1 remains unchanged.

In cycle $n + 1$, the priorities of the supply chain negotiators of clusters 1, 2 and 3 remain unchanged, assuming the values of all the attributes involved in decision-making are the same or similar to those of the previous cycle of computation. Cluster 1 will again impose some constraints on clusters 2 and 3, when they try to reschedule their local schedules. Cluster 1 remains unchanged.

If the local schedule of cluster 1 is locally feasible but not the global schedule of the entire manufacturing system, a deadlock occurs. As long as the schedule of cluster 1 remains unchanged in the subsequent cycles, no feasible global schedule can be found.

Some of the main rules in pseudo-English form are as follows.

Rule #1

If (loop number of rescheduling is less than the predefined maximum loop number)

Then (add 1 to loop number of rescheduling)

Rule #2

If (loop number of rescheduling is equal to the predefined maximum loop number)

Then (loop number of rescheduling equals 0)

And (return a randomly selected supply chain cluster ID)

7.5.3 System Output Generator

The system output generator comprises two functional sub-modules namely the scheduling information output and the agents monitor. The scheduling information output searches the scheduling database, which stores all the information involved in a scheduling problem, and displays the information required by users. Through the system output generator, users are able to access the scheduling database and browse the information of every processing stage.

The runtime status of the supervisory agent and the activated supply chain cluster agents can be obtained via the agents monitor. In summary, the system output generator is able to show the following information.

- (1) The optimal or near optimal schedule of different supply chain clusters;
- (2) The historical records of different scheduling problems and their results. This is useful for the choice of GA parameters for the current scheduling problem;
- (3) The run-time status of the activated supply chain cluster agents, the supervisory agent and the KBS.

7.5.4 Agents' Locale Provider

The agents' locale provider is a place for supply chain cluster agents to prioritise supply chain cluster negotiators, to reject or accept schedules generated, and to finalize the overall schedule, under the control of the supervisory agent. The activities carried out by the agents' locale provider are as follows.

- The supply chain cluster negotiator, which is the representative of a supply chain cluster agent, forwards its bid data to the supervisory agent, after a local optimal schedule for the supply chain cluster has been worked out;
- The supervisory agent works out the priority of supply chain cluster negotiators according to the bid data and decision-making policies. Some of the schedules generated are rejected as a result of the negotiations among supply chain cluster negotiators based on their priority; and
- The supervisory agent instructs the affected supply chain clusters, whose schedules have been rejected or whose scheduling problems have additional constraints added, to 're-schedule' so as to work out another local near optimal schedule.

7.6 Structure of the Supply Chain Scheduling Client System (SCSC)

The supply chain scheduling client System (SCSC) allows users to view the properties of supply chain clusters, and monitor the status of supply chain cluster agents and the

performance of the work order scheduling engine (Figure 7-6). Once the SCSC is invoked, it will establish communication with the SCSM. Subsequently, each supply chain cluster agent begins to retrieve all the necessary information relevant to the supply chain cluster which it belongs, from the scheduling database and domain knowledge base of the SCSM. This information is then kept in the local data store containing local scheduling information and domain knowledge respectively (Figure 7-2).

Briefly, the local scheduling information data store contains such information as supply chain unit-transportation-work order family that it represents, supply chain unit capacity and cycle time, GA parameters and the objective functions for the work order scheduling engine, schedule constraints imposed by other supply chain clusters, and local optimal schedule worked out by the work order scheduling engine.

Figure 7 - 6 Structure of supply chain scheduling client (SCSC)

Figure 7-6 shows the structure of the SCSC. Similar to the SCSM, a system configurator and a system output generator, which allow the interaction with the SCSC, have been incorporated.

The intelligent agent based SCOS is illustrated by a hypothetical 18 work orders from 3 customers and 4 supply chain virtual clusters as reported in Section 7.7.

7.7 Example and Discussions

Figure 7 - 7 Functional structure of the prototype SCOS

The functional structure of the SCOS module developed is shown in Figure 7-7. The *data input* provides the necessary functions to import data from files or to extract data from the RSO and SCVC modules. The *system configuration* allows the users to configure the supply chain clusters, supply chain scheduling master/client and the dynamic scheduler embedded.

The *network options* and *communication and information change protocols* can be defined for both supply chain scheduling master and client. Besides, decision making rules and the parameters used to solve the conflicts among software agents are configured in *decision making options* and the *bid evaluation options*. The *SCOS runtime* is used to control the running of the SCOS and monitor the status of the agents and the KBS inference engine. The order schedule and the schedule of individual supply chain units can be retrieved from the *SCOS result output*. It also provides the statistic data of the system and the function to export the results.

Figure 7-8 shows the supply chain and its units that are modelled in this example. It consists of 3 suppliers (SU01, SU02 and SU03), 6 manufacturing plants (MP1, MP2, MP3, MP4, MP5 and MP6), 4 assembly plants (AP01, AP02, AP03 and AP04), and 4 distribution centres (DC01, DC02, DC03 and DC04).

Figure 7 - 8 The overview of the supply chain in this example

Assume that based on the supply chain topology depicted in Figure 7-8 and the customer orders shown in Table 7-2, the RSO module has determined the work order routings and subsequently the SCVC module has assigned the supply chain units into four virtual clusters,

VC1, VC2, VC3 and VC4 (Table 7-1). Table 7-1 also indicates the manufacturing lines of a manufacturing plant. For example, the manufacturing plant, MP01, has two manufacturing lines namely M1L1 and M2L2; the manufacturing plant, MP03, has three manufacturing lines namely M3L1, M3L2 and M3L3.

Table 7 - 1 Supply chain virtual clusters and their supply chain units

Virtual Cluster 1 (VC1)		Virtual Cluster 2 (VC2)	
SU01		MP02	(M2L1,M2L2)
MP01	(M1L1,M1L2)	AP02	
MP05	(M5L1,M5L2)	DC02	
AP01			
DC01			
Virtual Cluster 3 (VC3)		Virtual Cluster 4 (VC4)	
SU02		MP04	(M4L1,M4L2,M4L3)
SU03		AP04	
MP03	(M3L1,M3L2,M3L3)	DC04	
MP06	(M6L1,M6L2)		
AP03			
DC03			

In this example, six products (P01, P02, P03, P04, P05 and P06) are to be completely processed by four supply chain clusters (VC1, VC2, VC3, and VC4) according to the sequence shown in Table 7-2. The tasks or jobs in each virtual cluster are uniquely identified. For example, Product P01 is processed through VC1 and VC3 in the job sequence 011-031 for work order WO11 of customer order CU01 from customer ABC Engineering. If one were to examine the schedule of a virtual cluster, say VC1, it would look like the one shown in Figure 7-9 which depicts the utilization of the sever supply chain units in the VC1 for all the 12 jobs (011, 012, 013, 014, 017, 018, 019, 01A, 01D, 01E, 01F and 01G). It needs to process 33 jobs in order to fabricate 6 products and fulfil the three customer orders. The local schedules of all the four virtual clusters are derived independently and are used to compare with the results obtained from SCOS.

Since most of the products are processed in more than one virtual cluster, it is clear that a global schedule has to be defined and optimized, even though the local schedule of each

supply chain unit is already optimized subject to its own constraints. In this example, the local schedules of the four virtual clusters have been optimized by a GA-enhanced dynamic scheduler for a population size of 60, crossover and mutation rates of 0.9 and 0.03 respectively, and 100 generations (Khoo *et al.* 2000, Yin 2000). The objective functions are cycle time, which is to be minimized, and the on-time delivery, which is to be maximized. For easy illustration and comparison, the dynamic scheduler partitions a day into 50 equal time intervals.

Table 7 - 2 Work order details of the example

Customer Order	Customer Name	Work Order	Product	Order Qty	Delivery Date	Job Id in VC1	Job Id in VC2	Job Id in VC3	Job Id in VC4
CU01	ABC Engineers	WO11	P01	20	15 Dec 2009	011		031	
		WO22	P02	10	15 Dec 2009	012			
		WO33	P03	15	15 Dec 2009	013	023		
		WO4A	P04	30	15 Dec 2009	01A	02A		04A
		WO5B	P05	20	15 Dec 2009			03B	04B
		WO6C	P06	30	15 Dec 2009			03C	
CU02	AA Pte Ltd	WO17	P01	20	16 Dec 2009	017		037	
		WO28	P02	10	16 Dec 2009	018			
		WO39	P03	15	16 Dec 2009	019	029		
		WO44	P04	30	16 Dec 2009	014	024		044
		WO55	P05	20	16 Dec 2009			035	045
		WO66	P06	30	16 Dec 2009			036	
CU03	BB Mold	WO1D	P01	20	16 Dec 2009	01D		03D	
		WO2E	P02	10	16 Dec 2009	01E			
		WO3F	P03	15	16 Dec 2009	01F	02F		
		WO4G	P04	30	16 Dec 2009	01G	02G		04G
		WO5H	P05	20	16 Dec 2009			03H	04H
		WO6I	P06	30	16 Dec 2009			03I	

Figures 7-9 to 7-11 show the schedules of VC1, VC2 and VC3 respectively before re-scheduling by the SCOS. Although the local schedules of virtual clusters are optimized for minimum cycle time, as mentioned earlier, conflicts among the local schedules can arise in the process of deriving an optimum global schedule. For example, it is clear from Figures 7-9 and 7-10 that, for Product P03 of WO39, Job 029 in VC2 can only start after completion of Job 019 in VC1. However, it can be seen obviously from Figures 7-10 and 7-11 that Job 029

(on manufacturing line M2L1) starts and ends much earlier than Job 019 (on manufacturing line M1L1). That is to say, Job 029 precedes Job 019. Similar conflicts arise for other jobs such as Job 014 (Figure 7-9) and Job 024 (Figure 7-10), and Job 017 (Figure 7-9) and 037 (Figure 7-11). Such conflicts arise because the local schedule is derived independently of other locally optimized virtual cluster schedules.

Figure 7 - 9 Example schedule of the VC1 with/without SCOS

Figure 7 - 10 Schedule of VC2 without SCOS

Figure 7 - 11 Schedule of VC3 without SCOS

Figure 7 - 12 Schedule of VC2 with SCOS

Figure 7 - 13 Schedule of VC3 with SCOS

Figure 7 - 14 Schedule of VC4 with SCOS

Figure 7 - 15 Schedule of the 18 work orders from 3 customer orders

After the intelligent agent based SCOS has re-scheduled all four virtual clusters in order to arrive at a near optimal global schedule, their local schedules are shown in Figure 7-9 and Figures 7-12 to 7-14 respectively. There is no change in the schedule of VC1 as all the jobs of VC1 have no constraints from other local schedules. It is clear from these Figures 7-12 to

7-14 that many supply chain units have many idle periods, giving rise to unduly long cycle time. It is due to the constraints imposed by the order of processing of the respective jobs in other virtual clusters as specified in Table 7-1 and the negotiation and conflicts solving among different supply chain virtual clusters. For example, consider the Job 019 in VC1 in Figure 7-9 again that finishes at around 240th time interval. As a result, Job 029 in VC2 in Figure 7-12 is forced to begin after the 240th time interval from the initial schedule in Figure 7-10, in which Job 029 begins at around 120th time interval, after negotiation among the various supply chain cluster agents. As shown, most of the jobs have been scheduled as early as possible. The final schedules are feasible and near-optimal, given the two objectives of minimizing cycle time and maximizing on-time delivery, subject to the constraints of due date and supply chain unit capacity. The overall schedule of 501 time intervals to fulfil the 18 work orders from 3 customers is shown in Figure 7-15.

7.8 Summary

An intelligent agent-based distributed architecture for supply chain order scheduling (SCOS), which is built on top of a dynamic scheduler, is presented. The intelligent agent-based SCOS consists of two subsystems namely the supply chain scheduling master (SCSM) and the supply chain scheduling client (SCSC). Two software agents, namely the supply chain supervisory agent (SCSA) and the supply chain cluster agents (SCCA), work out the global near-optimal schedule for a complex supply chain system consisting of multiple supply chain clusters that are derived from the SCVC module. The SCSM maintains all the domain knowledge and scheduling information in its database and can communicate with all the “virtual clusters” residing in the SCSC. The SCSC once invoked, establishes communication with the SCSM and retrieves the relevant information to schedule the individual supply chain virtual cluster, which is accomplished by the dynamic scheduler. The SCSM contains a knowledge base with production rules for decision-making and conflict or deadlock

resolution in multiple virtual clusters scheduling. The various supply chain cluster negotiators, assisted by the knowledge base, arrive at a near optimal global schedule for the entire manufacturing system.

The capability of the intelligent agent-based SCOS was illustrated by a hypothetical supply chain optimization problem with 18 work orders from 3 customers and 4 supply chain virtual clusters. The results show that the agent-based architecture of the SCOS can successfully resolve the conflicts among supply chain virtual clusters through negotiation and communication, and obtain a feasible, near-optimal global schedule for the entire supply chain.

Chapter 8 CASE STUDY: AN APPLICATION OF SCASO TO SEMICONDUCTOR PACKAGING INDUSTRY

8.1 Introduction

In this chapter, a case study based on a leading assembly and test service provider in semiconductor packaging industry in Singapore is discussed in detail to illustrate the effectiveness of the prototype SCASO system which has been realized using Microsoft Visual Studio and Java with the aid of a java-based expert system shell, Jess.

Semiconductor packaging provides the interconnection from the Integrated Circuit (IC) to the printed circuit board (PCB) and acts as an interface between circuit and the board. Additionally, packaging also provides the desired mechanical and environmental protection for the circuitry to ensure reliability and performance. Semiconductor packaging is labour intensive and this has resulted in the outsourcing of the assembly and test activities. The major location for the semiconductor packaging industry especially the subcontract packaging companies such as ASE, Amkor, SPIL and STATS ChipPAC is in the Asia Pacific region. The large subcontractors are able to provide assembly, test and turnkey services.

XYZ Company headquartered in Singapore is a leading service provider of semiconductor assembly and test. It is able to provide services to a diversified global customer base including the computing, communications, consumer, automotive and industrial markets. As an Outsourced Semiconductor Assembly and Test (OSAT) provider, XYZ Company is capable to provide a comprehensive turnkey solution that encompasses key building blocks of design, redistribution, wafer bump, probe, assembly, test and supply chain management to its customers. It has a global manufacturing presence spanning from Singapore, China, South

Korea, Malaysia, Taiwan, Thailand and the United States. Due to the sensitivity of the semiconductor industry, the data in the following case study are simplified and represented using alphanumeric codes.

8.2 The Supply Chain and the Process Flow

8.2.1 Overview of the Semiconductor Subcontract Environment and Its Supply Chain

Figure 8-1 shows a typical semiconductor subcontract (OSAT) environment. Basically, the customer orders the wafer from a wafer fab/foundry that fabricates the wafer based on the IC design through many complex and repeated sequential processes known as front-end processing. The IC is then created on a silicon substrate called wafer and the wafer lots will then be shipped to the semiconductor packaging factories for assembly and test. During the back-end processing phase, the IC chips are encapsulated into packages, and thoroughly inspected before becoming completed products. The finished goods (FG) will then be arranged for the shipment to the customer directly or to the PCBA plant/warehouse/DC through some drop shipping arrangement that can effectively eliminate the upfront inventory and other duplication efforts such as packing and shipping. The drop shipping is able to reduce the total inventory management and shipping costs.

Figure 8 - 1 A typical semiconductor subcontract (OSAT) environment

- **Wafer fab/foundry:** It is where all electronic components of a semiconductor are interconnected onto a single die of silicon. It provides a clean-room facility where wafers of silicon or other semiconductor substrates are manufactured based on the full IC layout design from customer. Wafers then become the raw materials for the IC fabrication process.
- **Materials supplier:** Semiconductor assembly and test utilizes and consumes many materials in addition to the wafer. The direct material is the materials that are required in assembly operations which create the IC leads and eventually encapsulate the chips, such as epoxy and lead frame for die attach operation, gold wire for wire bonding operation, and compound for mold operation. The packing material is used in the post test operations to pack IC components for shipment. Inspected IC components are stored in trays or tapes and labelled with the product information. The humidity indicator is frequently used to monitor the environment as certain level of humidity might degrade the quality of the IC components.
- **Vendor managed inventory (VMI):** In order to optimize the supply chain and inventory carrying cost, the supplier or vendor of a material sometimes becomes responsible for maintaining the customer's inventory levels to prevent the material shortage.
- **Semiconductor assembly and test:** It is where the semiconductor back-end packaging processes are carried out. The semiconductor assembly and test service provider normally maintains customer wafer lots in its own die bank if the wafer lot shipments arrive before the lot release instruction. Once receiving the instructions from customers, it will release the relevant wafer lots either in the die bank or in-transit as soon as the capacity and lots are available. It works out its own material purchase plan using the forecast data as the lead-time of some materials such as lead frame is as long as one month. This will ensure the minimal material shortage. After a lot released to the assembly and/or test line, the customer is informed the earliest possible FG and shipment date, so that the customer is able to make proper arrangement for shipment directly to the PCB assembly plants or other desired locations based on its shipment schedule and flight availability among cities.

8.2.2 Current Planning and Scheduling Practice of XYZ Company

XYZ Company has nine assembly and test facilities with different capacity and capability. They are strategically located near its major customers (Figure 8-2). It provides services such as wafer bump, flip chip, wafer level CSP (WLCSP), wafer sort, wafer probe, assembly, test, post test and drop shipping and serves more than 50 customers all over the world. Though none of the nine factories is able to support all the services, the company is still able to furnish the so-called full back-end turnkey services for a wide variety of electronics applications by combining the strength of each factory.

Figure 8 - 2 Geographic factory location and product flow in the supply chain

Table 8-1 further lists the service type(s) that each factory can support and the product type(s) that each factory is capable of and qualified to run. For example, Factory F1 is able to provide the services of assembly, test, WLCSP and capable to run both laminate and leaded products.

Table 8 - 1 List of factory capability

Service Type				Product Type			
<i>Factory</i>	<i>Assembly</i>	<i>Test</i>	<i>WLCSP</i>	<i>Wafer Bump</i>	<i>Flip Chip</i>	<i>Laminate</i>	<i>Leaded</i>
F1	Y	Y	Y			Y	Y
F2	Y	Y			Y	Y	Y
F3				Y			
F4	Y	Y			Y	Y	
F5	Y	Y					Y
F6	Y	Y	Y	Y		Y	Y
F7		Y					
F8			Y				
F9				Y			

Note: "Y" indicates the factory has the capability.

The factory's Industrial Engineering (IE) department is the main force of product planning with the help of the demand management team and the capacity planning team. They will sit down for more than two weeks of meetings and discussions through conference calls to coordinate in MS Excels and work out the committed product plan and customer commitments in weekly bucket for the current and next months and in monthly bucket for subsequent months. The main considerations in their mind are the capacity of each factory and the customer location.

On the other hand, the product scheduling is carried out in each factory separately without any coordination and consideration of the upstream and/or downstream requirements of a wafer lot in the supply chain. In most of the factories, the MS Excel is the only tool to help them on the scheduling and it takes the factory planner and scheduler a few hours a day to schedule the lots only for the key front-of-line operations, such as die attach and wire bound, and end-of-line operations, such as mold and marking. In the situation where a lot needs to be processed in Factory F1 for assembly and then moved to Factory F2 for test, post test and shipping, there is no visibility for Factory F2 if the lot is still processing in Factory F1. Similarly, Factory F1 also has no visibility of the capacity and schedule of Factory F2 that could help it better allocate the lot which is needed to be further processed in Factory F2.

Thus, when this research was carried out, the company did not have an optimized local schedule for individual factory, let alone the coordination and optimization of the schedule

along the supply chain.

8.3 Results and Discussions

Due to sensitivity, the information obtained is masked where necessary. The following assumptions are made.

- (1) The production lines of factories are limited to the lines shown in Table 8-2. Some factories may have more production lines that handle different package families. For example, Factory F2 has two assembly lines, F2A1 and F2A2, one flip chip line, F2F1, one test line, F2T1, and one post test line, F2P1. It also owns a die inventory, F2D1, and most of the dies are shipped from supplier F2S1.
- (2) Package families that involved in this case study are listed in Appendix A. The relationship of product type, package type and package family is also indicated.
- (3) Wafer bump/WLCSP services have been ignored. As an advanced packaging technique, the volume is not large at the moment comparing to other services. To simplify the modelling, the product lines providing these services have been ignored. It includes lines F3B1, F6B1, F9B1, F1W1, F6W1, and F8W1.
- (4) In the subcontract environment, the order due date is not important. The factory has to issue the wafer lots to the lines as soon as receiving customer's instruction. The customer normally requests the earliest possible release and shipment date of its IC components.
- (5) Wafer/die supply is considered while other materials such as direct materials and packing materials are ignored. In subcontract environment, the materials other than wafer lots are normally ordered and stored according to the forecast/demand planning to ensure the sufficient materials supply for a smooth production. There might be materials shortage due to the drastic demand variation or the human error.
- (6) As mentioned in Section 8.2, the status of a customer wafer lot might be in-die-bank or in-transit. It is assumed that in-transit lot needs one day for shipment to arrival and in-die-bank lots can be issued to the line any time though some inspection and quality

checking might be still requested. The shipment of the wafer lot from wafer fab might be affected by the shipment schedule and the flight availability. In this case study, such disturbances are ignored.

- (7) A lot might need to transfer from one factory location to another due to the different services that a factory can provide and the location of the customer. For example, a customer in Taiwan wants the turnkey products which include the assembly and test services, but the Taiwan factories do not provide assembly service. The products have to be shipped to China or nearby factories with assembly capability and shipped back to Taiwan factories for test and packing, and delivered to the customer eventually. One day transportation lead-time is introduced in the prototype system if a lot needs to move between two different locations. Similarly, the flight availability and other factors that might affect the transportation are ignored.
- (8) As the customer orders have been committed in production planning phase as described in Section 8.2.2, the factory commitment and the product routing is then determined. Thus, this case study only examines the supply chain virtual clustering and order scheduling modules

Table 8 - 2 Production lines and die supplier

Factory	Assembly	Test	Die inventory Die bank	Supplier (die)
F1	F1A1,F1W1	F1T1,F1P1	F1D1	F1S1
F2	F2A1,F2A2,F2F1	F2T1,F2P1	F2D1	F2S1
F3	F3B1			
F4	F4A1,F4A2,F4F1	F4T1,F4T2,F4P1	F4D1	F4S1
F5	F5A1	F5T1,F5P1		
F6	F6A1,F6W1,F6B1	F6T1,F6P1	F6D1	F6S1
F7		F7T1,F7P1		
F8	F8W1			
F9	F9B1			

Note: "A"-Assembly line; "B"-Wafer bump; "F"-Flip chip; "P"-Post test; "T"-Test location; "W"-WLCSP

8.3.1 Supply Chain Virtual Clustering Module (SCVC)

The details of the work orders and the processes are listed in Appendix B. The work orders and their processes can be converted into a Supply_Matrix shown in Table 8-3.

Table 8-4 lists the parameters used in the computation of the MBEA enabled SCVC which

Table 8 - 3 Supply_Matrix for Case Study of XYZ Company

Note: WO and SCU denote work orders and supply chain units respectively

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Table 8 - 4 Parameters used in simulation run

Parameters	Value	Description
Number_of_generation_for_parameter_updating	60	Number of GA generations between two consecutive TS for parameter updating
FC_c_Min	2	Minimal number of cluster of fuzzy c-means
FC_c_Max	6	Maximal number of cluster of fuzzy c-means
FC_c_Step_Min	1	Minimal step for neighbourhood search of parameter <i>c</i>
FC_c_Step_Max	2	Maximal step for neighbourhood search of parameter <i>c</i>
FC_m_Min	1.25	Minimal number of <i>m</i> of fuzzy c-means
FC_m_Max	3	Maximal number of <i>m</i> of fuzzy c-means
FC_m_Step_Min	0.01	Minimal step for neighbourhood search of parameter <i>m</i>
FC_m_Step_Max	0.3	Maximal step for neighbourhood search of parameter <i>m</i>
GA_number_of_generation	1200	Total number of GA generations
GA_population_size	500	GA population size
GA_crossover_rate	0.9	GA crossover probability
GA_mutation_rate	0.1	GA mutation probability
GA_elitist_rate	0.08	Percentage for GA elitist strategy
TS_number_of_individual	4	Number of GA populations for TS
TS_new_population_elitist_rate	0.2	Percentage of the best chromosome to be selected into the new population after TS parameter updating
TS_length_of_tabu_list	8	Tabu list length
TS_promise_level_weightage	1/0	The weightages for best and average promise level respectively

Figure 8 - 3 The best number of cluster centre of MBEA

Three supply chain unit-transportation-work order families (supply chain virtual clusters) have been formed and the work orders and supply chain units are evenly distributed to the three families. There are only four, WO51, WO52, WO61 and WOG1, out of the 23 work orders that are required to travel among clusters. A typical cluster as shown in Table 8-5

Table 8 - 5 Optimized supply chain virtual clusters in Supply_Matrix format

SCU WO	F4A1	F4A2	F4F1	F4F2	F4F3	F4F4	F4F5	F4F6	F4F7	F4F8	F4F9	F4F10	F4F11	F4F12	F4F13	F4F14	F4F15	F4F16	F4F17	F4F18	F4F19	F4F20	F4F21	F4F22	F4F23	F4F24	F4F25	F4F26	F4F27	F4F28	F4F29	F4F30		
	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
WOE1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WO91	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WOC1	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WOG1	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WOJ1	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WOL1	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WO54	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
WO21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0		
WO71	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0		
WO81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0		
WOB1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0		
WOH1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0		
WOK1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0		
WO53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0		
WO55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0		
WO61	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0		
WO11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	
WO51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	0	0	0	
WOA1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
WOD1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	
WOF1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	
WOM1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
WO52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0

8.3.2 Supply Chain Order Scheduler (SCOS)

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a near global optimal schedule.

Table 8-6 shows the three supply chain virtual clusters, namely VC01, VC02 and VC03, with their associated supply chain units transformed from the Supply_Matrix shown in Table 8-5. For example, VC03 consists of nine supply chain units, F1S1, F6S1, F1D1, F1A1, F6A1, F1T1, F6T1, F1P1 and F6P1. Two Die Attach (DA) machine types, i.e. DA01 for ALPHASEM machines and DA02 for ESEC machines, and two Wire Bond (WB) machine types, i.e. WB01 for KNS machines and WB02 for ASM Eagle machines, and one end of line (EOL1) are further modelled to represent the assembly line F2A2. In doing so, the detailed schedule on individual machine types can be worked out.

Similarly, since some of the work orders such as WO51, WO61 and WOG1 have been processed in more than one virtual cluster, it is clear that a global schedule has to be defined and optimized, even though the local schedule of each supply chain unit is already optimized subject to its own constraints. In the subsequent simulation runs, the parameters of the genetic algorithm of the dynamic scheduler are as follows: population size of 80, 200 generations, the probability of crossover and mutation are 0.9 and 0.03 respectively and the linear fitness ranking method and elitist selection are applied. The rule set based on scheduling attributes is adopted to do the decision-making and the objective function to be optimized is cycle time. Similar as the case study presented in Chapter 7, the dynamic scheduler partitions a day into 50 equal time intervals for easy illustration and comparison.

In this case study, 23 work orders from seven customers (Appendix B) are to be completely processed by the three supply chain clusters (VC01, VC02 and VC03) according to the process sequence shown in Table 8-7. Similar to the case study described in Chapter 7, the tasks or jobs in each virtual cluster are uniquely identified. For example, WO51 of customer LSI is processed through VC02 and VC03 in the job sequence 02A-033.

Table 8 - 6 Supply chain virtual clusters and their supply chain units

Virtual Cluster 1 (VC01)	Virtual Cluster 2 (VC02)	Virtual Cluster 3 (VC03)
F4S1	F2S1	F1S1
F4D1	F2D1	F6S1
F6D1	F2A1	F1D1
F4A1	F2A2	F1A1
	- DA01,DA02	
	- WB01,WB02	
	- EOL1	
F4A2	F2F1	F6A1
F4F1	F2T1	F1T1
F4T1	F7T1	F6T1
F4T2	F2P1	F1P1
F4P1	F7P1	F6P1
F5A1		
F5T1		
F5P1		

Table 8 - 7 Work order details of the case study

Work Order	Customer	Qty(k)	Die	Processes	Job Id In VC01	Job Id In VC02	Job Id In VC03
WO11	INTEL	20	F1D1	F1A1, F1T1,F1P1			032
WO21	SANDISK	30	F2S1	F2A1,F2T1,F2P1		022	
WO51	LSI	10	F2D1	F2F1,F6T1,F6P1		02A	033
WO61	NVIDIA	20	F6D1	F6A1,F6T1,F6P1	01A		038
WO71	TSMC	10	F2D1	F2A1,F7T1,F7P1		023	
WO81	IDT	15	F2S1	F2A1,F2T1,F2P1		024	
WO91	SONY	25	F4S1	F4A1,F4T1,F4P1	012		
WOA1	INTEL	30	F1S1	F1A1, F1T1,F1P1			034
WOB1	SANDISK	10	F2D1	F2A1,F2T1,F2P1		025	
WOC1	ANALOG	5	F4D1	F4A1,F4T1,F4P1	013		
WOD1	LSI	15	F6S1	F6A1,F6T1,F6P1			035
WOE1	LSI	20	F6D1	F5A1,F5T1,F5P1	011		
WOF1	NVIDIA	10	F6S1	F6A1,F6T1,F6P1			036
WOG1	TSMC	20	F4D1	F4A2,F7T1,F7P1	014	021	
WOH1	IDT	15	F2D1	F2A2,F2T1,F2P1		026	
WOJ1	SONY	25	F4D1	F4A2,F4T2,F4P1	015		
WOK1	IDT	10	F2S1	F2A2,F2T1,F2P1		027	
WOL1	SONY	5	F4S1	F4A2,F4T2,F4P1	016		
WOM1	INTEL	15	F1D1	F1A1, F1T1,F1P1			037
WO52	INTEL	10	F2D1	F2F1,F1T1,F1P1		02B	031
WO53	IDT	25	F2S1	F2F1,F2T1,F2P1		028	
WO54	SONY	25	F4D1	F4F1,F4T1,F4P1	017		
WO55	SANDISK	5	F2D1	F2F1,F2T1,F2P1		029	

Figures 8-4 to 8-6 shows the schedules of VC01, VC02 and VC03 respectively. Obviously, the work orders that require being processed by more than one virtual clusters, such as WO51,

WO61 and WOG1, have been scheduled properly without any conflicts on job start and end times. For example, Job 02A of work order WO51 ends its process on line F2F1 at 403rd time interval in VC02 (Figure 8-5). After 1 day of shipment from the time interval between 403 and 453 which is represented by TDL1 in VC03 (Figure 8-6), it continues the remaining processes on line F6T1 from time interval 453rd onwards. Appendix D lists the details of the entire work order schedules including their transpiration lead-time from wafer fab and the shipment lead-time from one factory location to another.

As shown in Figures 8-4 to 8-6, all the work orders and its relevant jobs have been scheduled as early as possible. The final schedules are feasible while all the conflicts that are considered in the model among local schedules are resolved. In VC02 in Figure 8-5, the schedules for DA and WB operations are detailed down to the machine group level that gives the production planner and scheduler more flexibility and visibility on how the capacity of each operation that is modelled in the system is consumed and whether there is any shortage. The overall schedule of 581 time intervals to fulfil the 23 work orders from 7 customers is shown in Figure 8-7.

Figure 8 - 4 Schedule of VC01

Figure 8 - 5 Schedule of VC02

Figure 8 - 6 Schedule of VC03

Figure 8 - 7 Overall schedule of the work orders

8.4 Summary

In this chapter, the effectiveness of the prototype SCASO system has been illustrated using a case study based on the data obtained from a leading semiconductor back-end assembly and test company. An overview of the semiconductor subcontract environment and its supply chain is presented followed by the current planning and scheduling practices of the XYZ Company. An optimization problem with 23 work orders and 30 product lines has been discussed in detail. The MBEA enabled SCVC has been employed to compartmentalize the large optimization problem into relatively small sub-problems. It successfully derived the optimal number of cluster centres as well as the three supply chain virtual clusters. The virtual cluster information is then forwarded to the intelligent agent based SCOS to activate the SCSCs and SCCAs. With the help of a dynamic scheduler and the supply chain cluster negotiators, the SCCAs carry out coordination and negotiation, and are able to reach a near optimal schedule for the entire supply chain under the supervision of the SCSA. The results derived from the SCVC and SCOS are reasonable and feasible. Thus, the case study has demonstrated the effectiveness and capability of the prototype SCASO system.

Chapter 9 CONCLUSIONS AND FUTURE WORK

9.1 Conclusions

This thesis presents a study on the realization of a hierarchical model and a framework for extended supply chain coordination and optimization. The study aims at providing a tool to facilitate the planning and detailed scheduling of supply chain units such as suppliers, manufacturing plants, warehouses and distribution centres for global manufacturing. A prototype supply chain coordination and schedule optimization system (SCASO) comprising three main modules, namely Routing and Sequence Optimizer (RSO), Supply Chain Virtual Clustering (SCVC) and Supply Chain Order Scheduler (SCOS), has been established. Additionally, a novel approach known as multiple populations search strategy based evolutionary approach (MBEA) that serves as a generic optimization methodology has been formulated. The MBEA has been embedded into the RSO module as well as the SCVC module. The MBEA enabled RSO is able to derive a compromised set of GA parameters and use them to achieve better optimization performance. On the other hand, the MBEA also enables the SCVC module to identify optimal fuzzy c-means parameters, c and m , and use them to derive near optimal supply chain clusters, i.e. unit-transportation-work order families.

More specifically, the RSO module is tasked to provide the SCVC module with a good routing and work order process sequence combination while taking into consideration the capacity of each supply chain unit, the business strategy and the customer requirements in order to maintain the required customer service level and competitiveness. The SCVC module uses the outputs of the RSO module as inputs, and attempts to compartmentalize a large-scale supply chain optimization problem that can hardly be solved by conventional

algorithms into manageable sub-problems. As for the SCOS module, it is built on top of an intelligent agent-based distributed architecture. It comes with an agent-based distributed intelligent coordination and scheduling mechanism that integrates scheduling with supply chain optimization.

9.1.1 Framework of a Distributed Hierarchical Model for Supply Chain Coordination and Optimization

As already mentioned, the framework of a distributed hierarchical model for supply chain coordination and optimization comprises three main modules, namely RSO, SCVC and SCOS. It enables:

- Generation of preferred routings, transportation modes and work order plan under the constraints of customer service level, cycle time and cost;
- Formation of supply chain unit-transportation-work order families using the proposed MBEA enabled fuzzy clustering approach;
- Integration of scheduling with supply chain optimization to provide a near global optimal schedule for the entire supply chain; and
- Realization of a mechanism, which enables fine-tuning of solutions using the feedback information obtained from the SCOS module. Specifically, the feedback information is forwarded to the SCVC module and the RSO module. A compliance measure that is embedded in these modules can be used to evaluate the performance of the modules.

9.1.2 Multiple Populations Based Evolutionary Approach (MBEA)

The RSO and SCVC modules utilize a hybrid evolutionary approach that combines the strength of Genetic Algorithms (GAs) and Tabu Search (TS) to achieve better performance. It is further enhanced by a multiple populations search strategy (MPSS). The architecture of the novel multiple populations search strategy based evolutionary approach (MBEA) provides:

- A generic optimization methodology that can be applied to solve different optimization problems.

- Multiple flexible layers that enables optimization of multiple objective functions. The innovative five layers of the MBEA, namely common data storage layer, MPSS layer, optimization algorithms layer, logic and computational layer, and application layer, are able to provide common heuristics that can be used to realize a generic optimization tool. The MBEA not only searches for the best solution for the physical optimization problem, but also optimizes the parameters for GAs and fuzzy c-means. These parameters help solve the optimization problem quickly and effectively.

9.1.3 Extended Graph Representation of a Supply Chain

A novel graph representation known as Supply_Graph has been proposed and implemented. The Supply_Graph can be employed to represent the complex work order routings and business processes from customer orders to suppliers. On a Supply_Graph, the nodes represent the supply chain units such as factories, DCs and warehouses, while the arcs between two nodes indicate the transportation methods. It has been shown that the Supply_Graph is able to provide an enabling infrastructure, which is generic, flexible and sophisticated enough to incorporate important supply chain features. These features include i) multiple level assembly; ii) various modes of transportation; iii) multiple split and merge of orders; iv) alternative locations or manufacturing sites for product and its components; v) cross boundary representation; and vi) other complex relationship that can be expressed by logical symbols to facilitate supply chain coordination and global schedule optimization.

It has also been shown that a Supply_Graph can be employed to model and depict the information about complex supply chain units, customer order routing and transportation in an efficient manner. It lays the foundation for modules such as the RSO and the SCVC. The conversion rules used to extract routings and transform a Supply_Graph into a Supply_Matrix have also been established. Such a matrix helps in channelling the data from Supply_Graph to the SCVC module for further processing.

9.1.4 Exact Schema Theorem

Goldberg's schema theorem is fundamental to Genetic Algorithms (GAs). However, it can only provide the lower boundary instead of the exact expected number of schemas in the next generation. In view of this, an in-depth study has been carried out to realize an exact schema theorem which can mathematically characterize the evolution of the population of a GA. This also helps to predict the future behaviour of a GA.

Furthermore, an investigation into the existence of optimal crossover and mutation probabilities has been conducted. It examines the crossover probability, p_c , and mutation probability, p_m , using the proposed exact schema theorem and the theory of extrema of functions of several variables. As two very important GA control parameters, p_c and p_m do affect the performance of GAs drastically. This work establishes that optimal p_c and p_m do not exist in most cases. Hence, a compromised pair of p_c and p_m may help improve the performance of GAs.

9.1.5 MBEA Enabled Heuristic for Routing and Sequence Optimization (RSO Module)

A work order may have multiple routings, which denote the flow of materials that captures the sequence in which materials move from suppliers (raw materials) to manufacturers (finished product), and to customers (delivery). Since the capacity of each supply chain unit, such as a manufacturing plant, is limited, a near optimal routing and a work order process sequence is necessary for a mix of work orders and products. Furthermore, management level strategies can be incorporated into the prototype system.

In many situations, the combination of multiple goals and constraints may result in an exponentially growing search space. It is quite difficult for conventional optimization methods such as calculus based or enumerative techniques to reach a near global optimal solution due to combinatorial explosion.

The RSO module has demonstrated the possibility of adopting a hybrid evolutionary approach to optimize routing and sequence of a supply chain with growing search space. In association with this, a novel chromosome representation scheme, new genetic operator to repair illegal chromosomes and flexible tabu list have been proposed and implemented. In addition, adaptive mutation probability for individuals in a generation has been employed to promote the diversification of the worst chromosomes. A reactive selection operator is designed to ensure proper propagation of each chromosome of a generation. As GAs require fine-tuning of GA parameters in order to obtain good results, the MBEA has been adapted and embedded into the RSO module. A so-called promise level that measures the performance of the GA parameters has been proposed and implemented. Through managing multiple populations in a GA run, it has been shown that the MBEA enabled RSO is able to dynamically search and update the GA parameters. The results from different examples have shown that MBEA enabled RSO is able to converge earlier and the fitness values have been improved.

9.1.6 A MBEA Enabled Supply Chain Virtual Clustering (SCVC Module)

A complex extended supply chain optimization problem, which involves various supply chain units such as customer orders, supply chain units, transportation and product flows, can hardly be solved by conventional algorithms due to combinatory explosion. An MBEA enabled fuzzy c-means approach has been established to reduce the complexity of the optimization problem while retain the constraints and the ability to derive near optimal solutions for the entire supply chain.

Using the MBEA enabled fuzzy c-means approach, supply chain units, transportation modes and customer orders are virtually and dynamically organized into different unit-transportation-work order families. A work order family can then be processed largely within its unit-transportation-work order family. It has been shown that computational efficiency can be improved, as a large-scale supply chain optimization problem has been compartmentalized

into a number of relatively small and manageable problems. In addition, a new fuzzy c-means validity index has been proposed and implemented specially for the SCVC module to automatically identify the optimal fuzzy c-means parameters, namely number of clusters, c , and the weighting exponent, m . From the examples discussed, the MBEA enabled SCVC is able to search for near optimal supply chain clusters through the determination of the optimal fuzzy c-means parameters, c and m . The necessity to pre-define suitable values for the parameters c and m of fuzzy c-means, which may not be known as a prior knowledge, has thus been eliminated.

9.1.7 An Intelligent Agent-Based Distributed Architecture for Supply Chain Order Scheduling (SCOS Module)

An intelligent agent-based distributed architecture for supply chain order scheduling, which is built on top of a GA based dynamic scheduler, has been established to schedule orders in a dynamic and distributed environment. Two subsystems namely the supply chain scheduling master (SCSM) and the supply chain scheduling clients (SCSCs) have been developed for the SCOS module. With the aid of a distributed architecture, the supply chain supervisory agent (SCSA) of SCSM and the supply chain cluster agents (SCCAs) of SCSCs can cooperate with each other to resolve conflicts and work out the global near optimal schedule for a complex supply chain system consisting of multiple supply chain clusters that are derived from the SCVC module.

The SCSM maintains all the necessary information and provides a negotiation locale for the supply chain cluster negotiators, which are the representatives of the SCCAs to resolve their conflicts with the aid of a decision-making module under the supervision of a SCSA. Four rule sets for the knowledge-based system have been developed to determine the priority of the supply chain clusters. They are the rule set based on predefined priority of the supply chain cluster, the rule set based on scheduling attributes of supply chain clusters, the rule set based on the weighted scheduling attributes of supply chain clusters, and the rule set for

deadlock resolution.

The SCSC, on the other hand, retrieves all the scheduling information and knowledge related to the various supply chain clusters from the SCSM. Each supply chain unit-transportation-work order family that is worked out by the SCVC module is represented by a supply chain cluster and its SCSC. It is used to determine the local near optimal schedule for every supply chain cluster. It also co-ordinates the activation of supply chain cluster agents and their negotiators, and controls the communication among the SCSA and SCCAs, so as to derive the feasible or the near optimal schedule for the entire supply chain according to the objectives and decision-making policies.

From the example discussed, the agent-based system of the SCOS module is able to successfully resolve the conflicts among supply chain virtual clusters through negotiation and communication, and obtain a feasible, near-optimal global schedule for the entire supply chain.

9.2 Contributions of the Work

The contributions of the work are summarized as follows.

- (1) Establishment of a hierarchical model and a framework for extended supply chain coordination and optimization (Yin and Khoo 2007b). It has been shown that a typical supply chain can be designed and modelled using the Supply-Chain Operations Reference (SCOR) model;
- (2) Formulation of a novel multiple populations search strategy based evolutionary approach (MBEA). The general and flexible layers that are built into the MBEA make it a generic optimization methodology and can be applied to solve different optimization problems;
- (3) Realization of a novel graph representation known as Supply_Graph to denote an extended supply chain. This includes the representation method and the logical

relationship among the nodes of a Supply_Graph. A Supply_Matrix Converter is also implemented that can transform a Supply_Graph into a Supply_Matrix. This provides an avenue for supply chain information integration.

- (4) Formulation of an exact schema theorem which can predict the expected number of copies of schemas in the subsequent GA generation and makes the prediction of future behaviour of GA possible. Furthermore, the existent of a compromised pair of crossover and mutation probabilities that can lead to a better performance of GA has been established;
- (5) Realization of a MBEA enabled RSO module to optimize the routing and sequence of a supply chain (Yin and Khoo 2007a);
- (6) Establishment of the supply chain virtual clustering module (SCVC) (Khoo and Yin 2003) to compartmentalize a complex large-scale supply chain. This helps in reducing the search space for a complex supply chain problem. The MBEA enabled SCVC can also used to determine the parameters for fuzzy c-means. This eliminates the necessity to pre-define these parameters; and
- (7) Establishment of an intelligent agent-based distributed architecture for supply chain order scheduling module. The intelligent agent-based SCOS is able to facilitate and promote the negotiation and coordination among supply chain clusters. As a result, near global optimal schedule for the entire supply chain including suppliers and manufacturing plants can be obtained.

9.3 Limitations and Future Work

Globalization has brought about keen competition. At the same time, enterprises have to deal with increasingly complex tasks. The supply chain of an enterprise needs to handle the flow of materials in one direction and concurrently, the flow of orders as well as money in the other direction. Accordingly, the flow of information in both directions may be enormous in terms of size and number of supply chain units. It is important to note that a change in any supply chain unit may create waves of fluctuations propagating throughout the supply chain.

This change could take place in any part of the supply chain including materials supply, manufacturing and assembly, inventory, transportation and demand. Dynamic and stochastic events associated with a supply chain may also make coordination and optimization extremely difficult. Accordingly, the limitations and constraints of the prototype system include

- (1) The proposed MBEA uses GA and TS as the two main building blocks. Although it is able to search for the near optimal p_c and p_m , determination of other parameters such as number of populations and number of generations is still done subjectively;
- (2) The prototype system is able to react to dynamic events within supply chain clusters. However, the life span of a supply chain cluster has to be defined as the dynamic events may affect the effectiveness of the existing supply chain clusters. A more flexible way to handle dynamic events and a methodology to determine the life span of a supply chain cluster need to be explored;
- (3) The research work is built upon a deterministic supply chain model. Uncertainties in the supply chain network can adversely affect its performance. For example, common events such as traffic jam or flight delay may create disruptions to materials supply and goods delivery; exaggerated demand from sales departments may cause inventory and production fluctuations; and
- (4) Supply chain is evolving very fast with new practices, techniques and philosophies. The prototype system may not be able to accommodate all of them.

Thus, some future works to improve the prototype SCASO system have been identified as follows.

- (a) A study to investigate how such parameters as number of populations and number of generations can affect the convergence rate and the performance of the proposed MBEA;
- (b) A study to explore the possibility of deriving a compromised pair of GA parameters using the exact schema theorem directly. In doing so, it is postulated that the efficiency

of the proposed MBEA can be improved;

- (c) A study on the theories and algorithms that can be used to integrate the Supply_Graph with the RSO and SCVC modules seamlessly;
- (d) A study to realize a reactive mechanism upon detecting dynamic events as well as a compliance measure to fine-tune the results obtained, and a more flexible way to handle dynamic events and a methodology to determine the life span of a supply chain cluster;
- (e) A study on how the stochastic nature of a supply chain can be incorporated into the prototype system to improve the results obtained; and finally,
- (f) A study to incorporate more supply chain practices and techniques such as inventory policies, vendor managed inventory, drop shipping, outsourcing and transportation policies into the prototype system.

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APPENDICES

Appendix A Product Relationship of XYZ Company

The following table shows the product type and package family relationship that are used in the case study.

Product Type	Package Type	Package Family
LAMINATES	CSP	FBGA
		FLGA
		WLFBGA
	WLCSP	WLFLGA
LAMINATES	FLIP CHIP	fcBGA
LAMINATES	PBGA	EBGA
		EPBGA
		PBGA
		TBGA
LEADED	QFP	BQFP
		DQFP
		LQFP
		MQFP
		TQFP
LEADED	SOP	MSOP
		SSOP
		TSOP
		TSSOP
LEADED	QFN	BCC
		QFN punch
		QFN sawn

Appendix B Work Orders of XYZ Company

Product Type	Package Type	Package Family	Work Order	Customer	Customer Code	Qty(k)	Die	Product Routing
LAMINATES	CSP	FBGA	WO11	INTEL	CU11	20	F1D1	F1A1, F1T1, F1P1
LAMINATES	CSP	FLGA	WO21	SANDISK	CU21	30	F2S1	F2A1, F2T1, F2P1
LAMINATES	FLIP CHIP	fcBGA	WO51	LSI	CU61	10	F2D1	F2F1, F6T1, F6P1
LAMINATES	PBGA	EBGA	WO61	NVIDIA	CU62	20	F6D1	F6A1, F6T1, F6P1
LAMINATES	PBGA	EPBGA	WO71	TSMC	CU71	10	F2D1	F2A1, F7T1, F7P1
LAMINATES	PBGA	PBGA	WO81	IDT	CU22	15	F2S1	F2A1, F2T1, F2P1
LAMINATES	PBGA	TBGA	WO91	SONY	CU42	25	F4S1	F4A1, F4T1, F4P1
LEADED	QFP	BQFP	WOA1	INTEL	CU11	30	F1S1	F1A1, F1T1, F1P1
LEADED	QFP	DQFP	WOB1	SANDISK	CU21	10	F2D1	F2A1, F2T1, F2P1
LEADED	QFP	LQFP	WOC1	ANALOG	CU41	5	F4D1	F4A1, F4T1, F4P1
LEADED	QFP	MQFP	WOD1	LSI	CU61	15	F6S1	F6A1, F6T1, F6P1
LEADED	QFP	TQFP	WOE1	LSI	CU61	20	F6D1	F5A1, F5T1, F5P1
LEADED	SOP	MSOP	WOF1	NVIDIA	CU62	10	F6S1	F6A1, F6T1, F6P1
LEADED	SOP	SSOP	WOG1	TSMC	CU71	20	F4D1	F4A2, F7T1, F7P1
LEADED	SOP	TSOP	WOH1	IDT	CU22	15	F2D1	F2A2, F2T1, F2P1
LEADED	SOP	TSSOP	WOJ1	SONY	CU42	25	F4D1	F4A2, F4T2, F4P1
LEADED	QFN	BCC	WOK1	IDT	CU22	10	F2S1	F2A2, F2T1, F2P1
LEADED	QFN	QFN punch	WOL1	SONY	CU42	5	F4S1	F4A2, F4T2, F4P1
LEADED	QFN	QFN sawn	WOM1	INTEL	CU11	15	F1D1	F1A1, F1T1, F1P1
LAMINATES	FLIP CHIP	fcBGA	WO52	INTEL	CU11	10	F2D1	F2F1, F1T1, F1P1
LAMINATES	FLIP CHIP	fcBGA	WO53	IDT	CU22	25	F2S1	F2F1, F2T1, F2P1
LAMINATES	FLIP CHIP	fcBGA	WO54	SONY	CU42	25	F4D1	F4F1, F4T1, F4P1
LAMINATES	FLIP CHIP	fcBGA	WO55	SANDISK	CU21	5	F2D1	F2F1, F2T1, F2P1

Appendix C SCVC Result of XYZ Company

The near optimal fuzzy cluster matrix U^* and cluster centres V^* for the case study is as follows.

U^*	***										***				
	$WO11$	$WO21$	$WO51$	$WO61$	$WO71$	$WO81$	$WO91$	$WOA1$	$WOB1$	$WOC1$	$WOD1$	$WOE1$	$WOF1$	$WOG1$	$WOH1$
C1	0.3317	0.3256	0.3333	0.3348	0.3348	0.3239	0.3360	0.3336	0.3283	0.3376	0.3316	0.3329	0.3309	0.3358	0.3293
C2	0.3328	0.3409	0.3322	0.3308	0.3351	0.3402	0.3303	0.3308	0.3401	0.3308	0.3319	0.3322	0.3297	0.3311	0.3390
C3	0.3356	0.3336	0.3345	0.3344	0.3301	0.3359	0.3337	0.3355	0.3316	0.3317	0.3365	0.3339	0.3395	0.3331	0.3317
	$WOJ1$	$WOK1$	$WOL1$	$WOM1$	$WO52$	$WO53$	$WO54$	$WO55$							
C1	0.3373	0.3286	0.3384	0.3302	0.3295	0.3267	0.3363	0.3292							
C2	0.3303	0.3385	0.3283	0.3309	0.3333	0.3417	0.3303	0.3395							
C3	0.3325	0.3328	0.3332	0.3389	0.3371	0.3316	0.3334	0.3313							
V^*	***														
	$F1A1$	$F1T1$	$F1P1$	$F1D1$	$F1S1$	$F2A1$	$F2A2$	$F2F1$	$F2T1$	$F2P1$	$F2D1$	$F2S1$	$F4A1$	$F4A2$	$F4F1$
C1	0.1302	0.1727	0.1727	0.0861	0.0441	0.1679	0.0845	0.1703	0.2917	0.2917	0.2578	0.1649	0.0907	0.1365	0.0452
C2	0.1275	0.1707	0.1707	0.0852	0.0422	0.1819	0.0907	0.1781	0.3209	0.3209	0.2668	0.1839	0.0842	0.1256	0.0421
C3	0.1336	0.1783	0.1783	0.0895	0.0441	0.1720	0.0856	0.1733	0.3006	0.3006	0.2579	0.1731	0.0859	0.1292	0.0432
	$F4T1$	$F4T2$	$F4P1$	$F4D1$	$F4S1$	$F5A1$	$F5T1$	$F5P1$	$F6A1$	$F6T1$	$F6P1$	$F6D1$	$F6S1$	$F7T1$	$F7P1$
C1	0.1359	0.0916	0.2275	0.1813	0.0911	0.0438	0.0438	0.0438	0.1309	0.1749	0.1303	0.0884	0.0863	0.0895	0.0895
C2	0.1263	0.0833	0.2096	0.1686	0.0833	0.0432	0.0432	0.0432	0.1267	0.1694	0.1272	0.0854	0.0844	0.0862	0.0862
C3	0.1292	0.0860	0.2152	0.1718	0.0865	0.0434	0.0434	0.0434	0.1337	0.1774	0.1337	0.0871	0.0901	0.0851	0.0851

Optimized virtual clusters for the case study are as follows.

SCU WO	F 1	F 4	F 1	F 4	F 4	F 4	F 4	F 4	F 4	F 5	F 5	F 5	F 6	F 7	F 7	F 2	F 2	F 2	F 2	F 2	F 2	F 2	F 1	F 1	F 1	F 1	F 6	F 6	F 6	F 6
	S	A	A2	F1	T1	T2	P1	D1	S1	A1	T1	P1	D1	T1	P1	A1	A2	F1	T1	P1	D1	S1	A1	T1	P1	D1	A1	T1	P1	S1
WO61	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
WO91	0	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOC1	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOG1	0	0	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOJ1	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOL1	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WO54	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WO22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0
WO71	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
WO81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0
WOB1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0
WOH1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0
WOK1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0
WO53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0
WO55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0
WO11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0
WO51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	1	0
WOA1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0
WOD1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
WOE1	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOF1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
WOM1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0
WO52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0

Note: WO and SCU denote work orders and supply chain units respectively

Noticed that WO61, WOE1 and F1S2 are not well placed by the SCVC, the second best clusters that are suggested by the near optimal fuzzy cluster matrix U^* and the cluster centre matrix V^* are then selected. Thus, the WO61, WOE1, F1S1 are re-allocated into cluster C3, C1 and C3 respectively. The re-arranged virtual clusters are as follows.

SCU WO	F 4 1	F 4 2	F 4 F1	F 4 T1	F 4 T2	F 4 P1	F 4 D1	F 4 S1	F 5 A1	F 5 T1	F 5 P1	F 6 D1	F 7 T1	F 7 P1	F 2 A1	F 2 A2	F 2 F1	F 2 T1	F 2 P1	F 2 D1	F 2 S1	F 1 S1	F 1 A1	F 1 T1	F 1 P1	F 1 D1	F 6 A1	F 6 T1	F 6 P1	F 6 S1
WOE1	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WO91	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOC1	1	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOG1	0	1	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOJ1	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WOL1	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WO54	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WO22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
WO71	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
WO81	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0
WOB1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0
WOH1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0
WOK1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	0	0	0	0
WO53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0
WO55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0
WO61	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
WO11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0
WO51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	0
WOA1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0
WOD1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
WOF1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
WOM1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0
WO52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	1	0	0	0	0	0

Note: WO and SCU denote work orders and supply chain units respectively

Appendix D Detailed Schedule of Work Orders

Work Order	Job	Start Date	Time	End Date	Time	Virtual Cluster	Line
WO21	022	2008-12-20	0	2008-12-20	1	VC02	F2S1
WO21	022	2008-12-20	1	2008-12-21	1	VC02	TSL1
WO21	022	2008-12-21	2	2008-12-24	2	VC02	F2A1
WO21	022	2008-12-24	26	2008-12-28	6	VC02	F2T1
WO21	022	2008-12-28	6	2008-12-28	36	VC02	F2P1
WO51	02A	2008-12-20	5	2008-12-20	6	VC02	F2D1
WO51	02A	2008-12-26	23	2008-12-28	3	VC02	F2F1
WO51	033	2008-12-28	3	2008-12-29	3	VC03	TDL1
WO51	033	2008-12-29	3	2008-12-30	13	VC03	F6T1
WO51	033	2008-12-30	13	2008-12-30	23	VC03	F6P1
WO52	02B	2008-12-20	3	2008-12-20	4	VC02	F2D1
WO52	02B	2008-12-20	43	2008-12-22	23	VC02	F2F1
WO52	02B	2008-12-23	16	2008-12-24	26	VC02	F2T1
WO52	02B	2008-12-24	26	2008-12-24	36	VC02	F2P1
WO52	031	2008-12-24	36	2008-12-25	36	VC03	TDL3
WO52	031	2008-12-25	46	2008-12-27	6	VC03	F1T1
WO52	031	2008-12-27	6	2008-12-27	16	VC03	F1P1
WO53	028	2008-12-20	3	2008-12-20	4	VC02	F2S1
WO53	028	2008-12-20	4	2008-12-21	4	VC02	TSL4
WO53	028	2008-12-22	23	2008-12-26	23	VC02	F2F1
WO53	028	2008-12-28	6	2008-12-31	6	VC02	F2T1
WO53	028	2008-12-31	6	2008-12-31	31	VC02	F2P1
WO54	017	2008-12-20	0	2008-12-20	1	VC01	F4D1
WO54	017	2008-12-20	1	2008-12-22	26	VC01	F4F1
WO54	017	2008-12-22	26	2008-12-25	26	VC01	F4T1
WO54	017	2008-12-25	26	2008-12-26	1	VC01	F4P1
WO61	01A	2008-12-20	1	2008-12-20	2	VC01	F6D1
WO61	038	2008-12-20	2	2008-12-21	2	VC03	TDL2
WO61	038	2008-12-22	1	2008-12-24	1	VC03	F6A1
WO61	038	2008-12-24	1	2008-12-26	21	VC03	F6T1
WO61	038	2008-12-26	21	2008-12-26	41	VC03	F6P1
WO71	023	2008-12-20	1	2008-12-20	2	VC02	F2D1
WO71	023	2008-12-20	2	2008-12-21	2	VC02	F2A1
WO71	023	2008-12-21	2	2008-12-22	12	VC02	F7T1
WO71	023	2008-12-22	12	2008-12-22	22	VC02	F7P1
WO81	024	2008-12-20	2	2008-12-20	3	VC02	F2S1
WO81	024	2008-12-20	3	2008-12-21	3	VC02	TSL2
WO81	024	2008-12-24	2	2008-12-25	27	VC02	F2A1
WO81	024	2008-12-25	27	2008-12-27	17	VC02	F7T1
WO81	024	2008-12-27	17	2008-12-27	32	VC02	F7P1
WO91	012	2008-12-20	0	2008-12-20	1	VC01	F4S1
WO91	012	2008-12-20	1	2008-12-21	1	VC01	TSL1
WO91	012	2008-12-21	1	2008-12-23	26	VC01	F4A1
WO91	012	2008-12-25	26	2008-12-28	26	VC01	F4T1
WO91	012	2008-12-28	26	2008-12-29	1	VC01	F4P1
WOA1	034	2008-12-20	0	2008-12-20	1	VC03	F1S1
WOA1	034	2008-12-20	1	2008-12-21	1	VC03	TSL1
WOA1	034	2008-12-23	26	2008-12-26	26	VC03	F1A1
WOA1	034	2008-12-27	6	2008-12-30	36	VC03	F1T1
WOA1	034	2008-12-30	36	2008-12-31	16	VC03	F1P1

Work Order	Job	Start Date	Time	End Date	Time	Virtual Cluster	Line
WOB1	025	2008-12-20	4	2008-12-20	5	VC02	F2D1
WOB1	025	2008-12-25	27	2008-12-26	27	VC02	F2A1
WOB1	025	2008-12-29	37	2008-12-30	47	VC02	F7T1
WOB1	025	2008-12-30	47	2008-12-31	7	VC02	F7P1
WOC1	013	2008-12-20	3	2008-12-20	4	VC01	F4D1
WOC1	013	2008-12-20	4	2008-12-20	29	VC01	F4A1
WOC1	013	2008-12-20	29	2008-12-21	9	VC01	F4T1
WOC1	013	2008-12-21	9	2008-12-21	14	VC01	F4P1
WOD1	035	2008-12-20	1	2008-12-20	2	VC03	F6S1
WOD1	035	2008-12-20	2	2008-12-21	2	VC03	TSL2
WOD1	035	2008-12-24	1	2008-12-25	26	VC03	F6A1
WOD1	035	2008-12-26	21	2008-12-28	11	VC03	F6T1
WOD1	035	2008-12-28	11	2008-12-28	26	VC03	F6P1
WOE1	011	2008-12-20	0	2008-12-20	1	VC01	F6D1
WOE1	011	2008-12-20	1	2008-12-22	1	VC01	F5A1
WOE1	011	2008-12-22	1	2008-12-24	21	VC01	F5T1
WOE1	011	2008-12-24	21	2008-12-24	41	VC01	F5P1
WOF1	036	2008-12-20	0	2008-12-20	1	VC03	F6S1
WOF1	036	2008-12-20	1	2008-12-21	1	VC03	TSL3
WOF1	036	2008-12-21	1	2008-12-22	1	VC03	F6A1
WOF1	036	2008-12-22	1	2008-12-23	11	VC03	F6T1
WOF1	036	2008-12-23	11	2008-12-23	21	VC03	F6P1
WOG1	014	2008-12-20	2	2008-12-20	3	VC01	F4D1
WOG1	014	2008-12-23	2	2008-12-25	2	VC01	F4A2
WOG1	021	2008-12-25	2	2008-12-26	2	VC02	TDL1
WOG1	021	2008-12-27	17	2008-12-29	37	VC02	F7T1
WOG1	021	2008-12-29	37	2008-12-30	7	VC02	F7P1
WOH1	026	2008-12-20	0	2008-12-20	1	VC02	F2D1
WOH1	026	2008-12-20	1	2008-12-20	26	VC02	DA01
WOH1	026	2008-12-20	26	2008-12-21	1	VC02	WB02
WOH1	026	2008-12-21	1	2008-12-21	26	VC02	EOL1
WOH1	026	2008-12-21	26	2008-12-23	16	VC02	F2T1
WOH1	026	2008-12-23	16	2008-12-23	31	VC02	F2P1
WOJ1	015	2008-12-20	1	2008-12-20	2	VC01	F4D1
WOJ1	015	2008-12-20	2	2008-12-22	27	VC01	F4A2
WOJ1	015	2008-12-22	27	2008-12-25	27	VC01	F4T2
WOJ1	015	2008-12-26	1	2008-12-26	26	VC01	F4P1
WOK1	027	2008-12-20	1	2008-12-20	2	VC02	F2S1
WOK1	027	2008-12-20	2	2008-12-21	2	VC02	TSL3
WOK1	027	2008-12-21	2	2008-12-21	17	VC02	DA02
WOK1	027	2008-12-21	17	2008-12-21	32	VC02	WB01
WOK1	027	2008-12-21	32	2008-12-22	2	VC02	EOL1
WOK1	027	2008-12-22	12	2008-12-23	22	VC02	F7T1
WOK1	027	2008-12-23	22	2008-12-23	32	VC02	F7P1
WOL1	016	2008-12-20	1	2008-12-20	2	VC01	F4S1
WOL1	016	2008-12-20	2	2008-12-21	2	VC01	TSL2
WOL1	016	2008-12-22	27	2008-12-23	2	VC01	F4A2
WOL1	016	2008-12-25	27	2008-12-26	7	VC01	F4T2
WOL1	016	2008-12-26	26	2008-12-26	31	VC01	F4P1
WOM1	037	2008-12-20	0	2008-12-20	1	VC03	F1D1
WOM1	037	2008-12-20	1	2008-12-21	26	VC03	F1A1
WOM1	037	2008-12-21	26	2008-12-23	16	VC03	F1T1
WOM1	037	2008-12-23	16	2008-12-23	31	VC03	F1P1