Supply Chain Management Optimization Using Meta-Heuristics Approaches Applied to a Case in the Automobile Industry

by

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THESIS PRESENTED TO ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
IN PARTIAL FULFILLMENT FOR A MASTER'S DEGREE WITH
THESIS IN MECHANICAL ENGINEERING
M.A.Sc.

MONTREAL, SEPTEMBER 6th, 2018

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
UNIVERSITÉ DU QUÉBEC

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ACKNOWLEDGMENT

I would like to thank my supervisors, Prof. Françoise Marchand and Prof. Thien-My Dao introduced me to the field of supply chain management and dedicated a lot of their time in helping me become a better researcher. I am profoundly grateful for their support, valuable recommendations, encouragement and useful suggestions throughout this research process. Not only my thesis, but also my writing style and academic aptitude has improved considerably as a result of their effort. I would not have been able to finish this wonderful thesis without their support and guidance.

I also like to thank the Ministry of Higher Education in Libya and Zawia Higher Institute of Science and Technology for awarding me with a full scholarship and covering all my expenses to facilitate my study abroad. I promise that I will best represent my country and serve my nation by proficiently assisting the next generation.

My deepest thanks go to my parents who devoted their life to encourage and support me as well as my wife who is always besides me during my happy and sad moments. I also want to thank the committee members Prof. Tony Wong and Prof. Yvan Beauregard for evaluating my thesis and for their relevant comments and suggestions that improve my research.

Finally, this acknowledgment would be incomplete if I did not thank all the other people who helped in making this work a success and a project I am proud of. This includes fellow research students at my ÉTS University, authors who were a great inspiration to me, and researchers who made their work accessible to motivate others.

OPTIMISATION DE LA GESTION DE LA CHAÎNE D'APPROVISIONNEMENT APPROCHES META-HEURISTIQUES APPLIQUEES A UN CAS DANS L'INDUSTRIE AUTOMOBILE

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RÉSUMÉ

Cette thèse présente l'optimisation de la gestion de chaînes d'approvisionnement avec des approches méta-heuristiques, en particulier pour la configuration d'un réseau de distribution multi-étages générique, pour la détermination d'un problème de livraison de type « tournée d'un laitier » avec une gestion lean de la chaîne d'approvisionnement. En effet, cette question peut être représentée comme l'itinéraire du véhicule d'approvisionnement ou de livraison de plusieurs collectes ou livraisons sur une base régulière et à différents endroits.

Le modèle optimal de livraison de « tournée d'un laitier » doit viser à améliorer la charge du véhicule et à minimiser la distance de transport (itinéraire optimal de livraison) entre les installations tout en optimisant la livraison complète des marchandises entre les installations de la chaîne d'approvisionnement. L'ensemble des approches méta-heuristiques et méta-heuristiques hybrides présentées dans ce mémoire vise à devenir un système de modélisation afin de trouver une solution optimale pour la distance de transport ainsi qu'une fréquence de livraison optimale pour gérer le transport de marchandises dans des réseaux logistiques hautement complexes. En fait, la distance de transport optimale garantit que le coût total de l'ensemble de la chaîne d'approvisionnement est minimisé.

En particulier, ce système de modélisation regroupe des concepts de gestion intégrée de la chaîne d'approvisionnement, proposés par des experts en logistique, des praticiens de la recherche opérationnelle et des stratèges. En effet, il fait référence à la coordination fonctionnelle au sein de l'entreprise, entre l'entreprise et ses fournisseurs et aussi entre l'entreprise et ses clients. Il fait également référence à la coordination inter temporelle des décisions relatives à la chaîne d'approvisionnement en ce qui concerne les plans opérationnels, tactiques et stratégiques de l'entreprise.

Le problème de livraison de la « tournée d'un laitier » est étudié avec l'approche de l'algorithme génétique ainsi qu'avec une approche hybride de l'algorithme génétique et l'approche d'optimisation de colonies de fourmis. Plusieurs cadres, modèles, approches méta-heuristiques et approches méta-heuristiques hybrides sont présentés et discutés dans cette thèse. Une étude de cas pertinente, issue de l'industrie automobile, est également présentée pour démontrer l'efficacité des approches proposées.

Enfin, l'objectif de cette thèse est de présenter une approche d'algorithme génétique et aussi une approche hybride de l'algorithme génétique combiné avec l'approche d'optimisation inspirée des colonies de fourmis, pour minimiser le coût total de la chaîne d'approvisionnement.

Cette approche hybride de l'algorithme génétique et de l'optimisation de colonies de fourmis peut efficacement trouver des solutions optimales. Les résultats de la simulation démontrent que cette approche hybride est légèrement plus efficace que l'algorithme génétique seul pour l'itinéraire optimal de livraison (tournée d'un laitier) qui permet d'obtenir le coût total minimum de la chaîne d'approvisionnement dans le cas étudié issu de l'industrie automobile.

Mots-clés: Chaîne D'approvisionnement, Optimisation, Tournée d'un laitier, Méta-Heuristique Hybride, Algorithme génétique, Optimisation de Colonies de Fourmis.

SUPPLY CHAIN MANAGEMENT OPTIMIZATION USING META-HEURISTICS APPROACHES APPLIED TO A CASE IN THE AUTOMOBILE INDUSTRY

Marwan HFEDA

ABSTRACT

This thesis presents supply chain management optimization with meta-heuristics approaches, specifically on issues regarding the configuration of a generic multi stage distribution network, and the determination of a milk-run delivery issue in lean supply chain management. Indeed, this issue can be represented as the routing of the supply or delivery vehicle to construct multiple pick-ups or drop-offs on a regularly scheduled basis and at different locations.

The optimal model for this milk-run delivery issue must aim to improve vehicle load and minimize transportation distance (optimal delivery route) between facilities while optimizing the entire delivery of goods among the supply chain facilities. The set of meta-heuristics approaches and hybrid meta-heuristics approaches introduced in the present research aim to become a modeling system to find an optimal solution for the transportation distance as well as the optimal delivery frequency for managing the transportation of goods in highly complex logistic networks. In fact, the optimal transportation distance ensures that the total cost of the entire supply chain is minimized.

In particular, this modeling system groups concepts about integrated supply chain management proposed by logistics experts, operations research practitioners, and strategists. Indeed, it refers to the functional coordination of operations within the firm itself, between the firm and its suppliers as well as between the firm and its customers. It also references the inter-temporal coordination of supply chain decisions as they relate to the firm's operational, tactical and strategic plans.

The milk-run delivery issue is studied two ways: with the Genetic Algorithm approach and with the Hybrid of Genetic Algorithm and the Ant Colony Optimization approach. Various frameworks, models, meta-heuristics approaches and hybrid meta-heuristics approaches are introduced and discussed in this thesis. Significant attention is given to a case study from the automobile industry to demonstrate the effectiveness of the proposed approaches.

Finally, the objective of this thesis is to present the Genetic Algorithm approach as well as the Hybrid of Genetic Algorithm with Ant Colony Optimization approach to minimize the total cost in the supply chain.

This proposed Hybrid of Genetic Algorithm along with the Ant Colony Optimization approach can efficiently and effectively find optimal solutions. The simulation results show that this hybrid approach is slightly better efficient than the genetic algorithm alone for the milk-run delivery issue which allows us to obtain the minimum total automobile industry supply chain cost.

Keywords: Supply Chain, Optimization, Milk-run, Hybrid Meta-heuristics, Genetic Algorithm, Ant Colony Optimization.

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LIST OF ABREVIATIONS

ACO	Ant Colony Optimization
AICS	Automobile Industry Case Study
CRM	Customers Relationship Management
GA	Genetic Algorithm
GDP	Gross Domestic Product
HAT	Hybrid Ant Colony Optimization and Tabu Search
HGA	Hybrid Genetic Algorithm and Ant Colony Optimization
IT	Information Technology
JIT	Just-In-Time
LM	Lean Manufacturing
LP	Linear Programming Problem
LSC	Lean Supply Chain
MIP	Mixed Integer Programming
OTD	Long Order-To-Delivery
SC	Supply Chain
SCM	Supply Chain Management
SPT	Shortest Processing Time
SRM	Suppliers Relationship Management
TS	Tabu Search
TSP	Travelling Salesman Problem

LIST OF SYMBOLS

Dc	Productivity/Demand Rate from Customers
dij	Transportation Distance from Facility i to Facility j
dr	Total transportation distance for one route
E	Evaporation Rate
F	Number of facilities
FDC	Delivery start-up cost
FOC	Order fixed cost of parts;
FOC’	Order fixed cost of finished products
i	nth Manufacturing plant /customer/ supplier facility
j	nth Manufacturing plant /customer/ supplier facility
K	Number of customers
M	Number of ants (Population Size)
N	Number of suppliers
n	Delivery frequency
P_m	Productivity/demand rate from a manufacturing plant
P_s	Productivity/demand rate from suppliers
Q	Constant value
SI_m	Part safety stock quantity of a manufacturing plant
SI_s	Part safety stock quantity of suppliers
SI'_c	Finished safety stock quantity of customers
SI'_m	Finished safety stock quantity of a manufacturing plant
T	Manufacture’s production cycle (30 days)
TC	Minimum total cost of supply chain
UDC	Unit delivery cost (5$ / km)
UIC_d	Parts unit inventory cost of in-transit
UIC_m	Parts unit inventory cost of a manufacturing plant
UIC_s	Parts unit inventory cost of suppliers
UIC'_c	Finished product unit inventory cost of customers
UIC'_d	Finished product unit inventory cost of in-transit

UIC'_m	Finished product unit inventory cost of a manufacturing plant
UPC_m	Unit production cost of manufacturing plant
UPC_s	Unit production cost of suppliers
USC_m	Production start-up cost/batch of a manufacturing plant
USC_s	Production start-up cost/batch of suppliers
V	Average speed of delivery vehicle (50 km/h)
W	Delivery vehicle capacity (20 tons)
W	Weight (mass) of part (kg)
w'	Weight (mass) of finished product (kg)
α	Pheromone exponential weight
β	Heuristic exponential weight

INTRODUCTION

The concept of supply chain management (SCM) has become essential in today's economy and in several industrial sectors due to its impact on firms' competitive edge. SCM is often put under pressure by firms striving to ensure high customer service levels while being forced to minimize costs and maximize profit margins (Altiparmak et al., 2009). Nowadays, the term "supply chain management" is more utilized than the term "logistics" for several reasons. Namely because traditional logistic activities only involve: distribution, purchasing, inventory management and maintenance while supply chain management also includes finance, marketing and customer service and product development (Bowersox et al., 2010). In SCM the provider and customers are connected throughout the entire process. They relate from the initial production stages when the supplier is working with the raw materials to the consumption of the product by the end user. Furthermore, a supply chain is a set of facilities that include supplies, purchasing, distribution, products and methods of controlling inventory and customers. In the supply chain, the flow of materials / products between a supplier and customer passes through several stages, and each stage may involve many facilities (Sabri et al., 2000).

According to Vonderembse et al (2006) competition has predominantly shifted from using firm orientation to supply chain orientation, thus supply chain improvement has become essential for survival. For instance, the automobile industry is ever changing, fast paced and requires a large capital. Thus, optimization tools that improve decision making, strategic planning and cost reduction are highly valuable for these challenges in SCM. Every supply chain is unique and demands a model that is customized to correspond the particular situation in the firm (D'este, 2001). Consequently, researchers increasingly propose the execution of "lean" in the supply chain as a way to get the required competitive advantage (Cudney et al., 2011).

The lean supply chain management (LSCM) strategy applies to each stage within the supply chain facilities including: suppliers, manufacturing plants, distributors, retailers and customers. Many studies conducted by practitioners and researchers have found that lean in the supply chain is a transformation process which makes firms more competitive. Studies and research show that the attributes and outcomes of applying lean in the supply chain (LSC) yields a better way of understanding the required competitive advantage in SCM. LSC is found to be linked to the following benefits: improved delivery, reduced cost, and the prevention of stock shortages. These things allow for high flexibility, improve product quality and customer service. Supply chain total cost includes marketability, distribution, production, storages, transportation, operations and the cost of initial facility (Nguyen et al., 2015). Successful SCM needs cooperative integration among all the facilities / partners in the entire SCM. Otherwise, the SCM will suffer with excessive stock / stock shortages, wrong demand forecasts, futile sales efforts and poor inventory management. Ultimately, all these poor activities result in poor customer service and high supply chain cost.

In order to survive and develop under the fierce pressure of globalization, enterprises relentlessly seek measures to enhance the performance of their supply chain (SC). Among several SC models that have been studied and applied, lean supply chain (LSC) is interpreted as an "ideal SC" owing to its ability to supply–finished products / services to consumers promptly, economically and in a seamless manner (Srinivasan, 2012). Similarly, Anand et al (2008) summarize that lean manufacturing (LM) tools / techniques are used to transform the traditional SC into LSC. SC is a complex network with multiple levels such as suppliers, manufacturers, warehouses, distributors, retailers, and customers. Thus, the optimization of supply chain management requires managing conflicting decisions, coordination and integration with respect to response time, and handing product variability. The problems associated with supply chain may be approached using mathematical modeling and optimization. The biggest challenge of SCM is to provide high quality of products with high level of service at cost efficiency.

Furthermore, LSC is attained when lean manufacturing concepts are applied within the organization (Paschal et al., 2012). According to Anand et al (2008) the milk-run delivery system is one of the most prevalent lean manufacturing techniques used to transform a supply chain into lean supply chain. The milk-run technique reduces wastage related to inventory, saves the total cost incurred and speeds out the flow of materials between the facilities involved in the supply chain (Miao et al., 2011).

Toyota and Seven-Eleven are international success stories of the milk-run application. The milk-run logistics refers to a concept that originates from the daily industry where one truck covers the input and output requirements of several stations using a predefined route and schedule. It is also inherent in American culture where the milkman distributes bottles on a daily basis (Ma et al., 2012). In this case, he follows a daily routine where full bottles are distributed, and the empty ones collected along his route. At the end, the milkman returns with the empty bottles to his milk facility location.

In optimization problems, Genetic Algorithm (GA) and Ant Colony Optimization (ACO) have been known as good approaches. Genetic Algorithm (GA) is designed to implement the natural evolution process, while ACO is inspired by the behaviour of real ant. (GA) is one of the most powerful meta-heuristics approaches based on the process of natural evolution (Bagheri et al., 2008). The survival of the fittest idea is adopted to provide a different examination method. It explores selected reasonable solutions that work together to achieve a good result. Heuristics are adaptive tools that ignore information to make fast and frugal decisions that are reduce or limit the search for solutions and robust under conditions (Mousavi et al., 2017). Additionally, “the metaheuristics approaches are considered as heuristic and randomization together. Furthermore, "the metaheuristics formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions” (Osman and Laporte, 1996). The main goal of this thesis is to explore and demonstrate how incorporating GA with ACO into a hybrid meta-heuristics approaches solves problems in the automobile industry. In other words, both approaches are combined into one in order to obtain near optimal or optimal solution.

The work of this thesis has been published in the Journal of Management and Engineering Integration (Hfeda, M et al., 2017). Particularly, this thesis is organized as follows. Chapter 1 explains essential definitions required for the reader to understand the studied topic and reviews literature concerning SCM by presenting related studies in this area. Chapter 2 presents an overview on optimization meta-heuristics approaches and mathematical modeling of SCM optimization. Chapter 3 presents the problematic of the automobile industry and results of testing both Genetic Algorithm (GA) and hybrid Genetic Algorithm (GA) with Ant Colony Optimization approaches (ACO) which are studied in this research. Then, we discuss obtained solutions as well as express the conclusions and propose future work.

CHAPTER 1

SUPPLY CHAIN MANAGEMENT

1.1 Objectives of Research Subject

In general, the purpose of this thesis is to identify a framework for optimization of supply chain management. It is based on the identified characteristics of supply chain management optimization and processes of SCM optimization. All supply chain functions including supplier, manufacturing, warehousing, and transportation have to align their strategies to minimize total functional cost. Simply put, optimization approaches are used to improve the relationships within firm and stages across the SC.

In particular, the three main objectives of this thesis are as follows:

1. Model a supply chain management problem.
2. Propose an approach for solution using the meta-heuristics.
3. Validate the proposed approach by a case study: automobile industry supply chain.

1.2 Literature Review

The literature review has focused on identifying essential definitions required for the reader to understand the research studied. In recent years, extensive research has been conducted in areas such as supply chain management, optimization and meta-heuristics by presenting various studies. In this section of the thesis, we describe supply chain management, optimization models, driver models and the solution methods.

The evolution of the concept of SCM can be dated back to 1950s, a period commonly referred to as the logistics era. At that time, the SCM concept was not valued as a strategic function (Ballou, 1978). However, in the early 1960s, the importance of logistics was established due to the recognition of physical distribution management as a separate function unto itself (Heskett et al., 1964). The period was known as the first transformational era. Most importantly, the concept of SCM was first presented by logistics consultants in the

1980s (Oliver et al., 1992). This meant that the SC could be viewed as a single entity and that the top-level management was entitled to make decisions. The concept was universally accepted by logistics experts and marketing theorists who focused on managing all the processes that are required to provide the customer with value and to expand the understanding of logistics (Gripsrud et al., 2006). Today, SCM has evolved to become an important management function that affects the ability of organizations to run profitable enterprises. According to Christopher (1992), "leading-edge companies have realized the real competition is not company against company, but rather supply chain against supply chain".

A lot of definitions have been proposed regarding the concept of supply chain management but most of them agree that it is goal is to coordinate activities within the firm to create value for the customers. It also integrates, manages and is responsible for the flow of materials by coordinating the whole materials process. In addition, it requires joint relationships with several organizational functions and several types of partners. According to Monczka et al (1998) SCM's "primary objective is to integrate and manage the sourcing, flow, and control of materials using a total systems perspective across multiple functions and multiple tiers of suppliers." Nevertheless, there is no generally accepted definition for the term "supply chain management". Therefore, Christopher (1992) defined the supply chain as a network of organizations involved in different processes that create value for the customer through upstream and downstream linkages. His definition touched on manufacturers, suppliers, vendors, wholesalers, retailers and the customer. In a general outlook, the supply chain is the network of entities through which materials flow. Those entities may include manufacturing sites, suppliers, distribution centers, carriers, retailers, and customers (Lummus et al., 1997). In addition, "the supply chain considers all of the following activities: sourcing, procurement, production scheduling, transportation, warehousing, inventory management, order processing, and customer service. Basically, everything associated with moving materials / products from the raw materials stage through to the customers" (Quinn, 1997).

In recent years, modeling and optimizing complex SCM systems have gained increasing popularity among researchers due to expanding competition, changing customer demands, shorter product lifecycles, rising product and market complexity. Thus, optimizing SCM frameworks can provide some critical support for decision making in a competitive market.

The fundamental approaches to modelling and optimizing supply chain management can be divided into five distinct classes according to Dong (2001) as following:

1- Fundamental formulation of supply chains.

2- Stochastic programming.

3- Integer-mixed programming.

4- Heuristic techniques.

5- Simulation-based methods.

These approaches are very valuable alternatives for solving large-scale problems efficiently because traditional simulation techniques for modeling and optimizing complex SCM require huge amounts of computing resources (Sanchez et al., 2007). Thus, meta-heuristics approaches and related methods are widely used for an optimization SCM. As firms have become conscious of the significance of supply chain performance and operational performance progress as well as integration and coordination of the distribution and production operations have been acknowledged as the competitive advantage source. The objective of an optimization SCM is to determine the best combination of parameters for the job, optimize activities in a SC and provide the best solutions to the problems at hand. However, this task can be very complex (Ateme-Nguema et al., 2007).

Meta-heuristics approaches could ensure the determination of a feasible solution for any given set of requests and enable the firm to address the highly complex problems within their supply chain management. Thus, these approaches can provide approximate solutions which are usually very near to optimal solutions. However, if a problem can be solved in polynomial time by classical optimization methods, it would be the best option to find optimal solutions. The meta-heuristics approaches might be effectively adjusted to address distinctive problems. What is more they could achieve very good results that might not be discovered through the utilization of classical optimization methods like the simplex method and the gradient descent method, etc. The simplex method, in mathematical optimization, is a well-known algorithm used for linear programming. This method presents an organized strategy for evaluating a feasible region's vertices that is used to eradicate the issues in linear programming. On the other hand, if a problem has exponential complexity, then with the present computational power, heuristic techniques may find good solutions within a reasonable time. In this case, classical optimization techniques may be unable to find optimal solutions for such complex problem. Meta-heuristics approaches have many advantages; most of meta-heuristics approaches use a certain exchange-off between randomization and local search, but most of all meta-heuristics approaches tend to be suitable for global optimization. Meta-heuristics approaches are applied to solve a large variety of problems and they find optimal solutions to complex issues in a reasonably short amount of computing time. However, there is no guarantee that optimal solutions can always be obtained. Furthermore, these approaches are limited in that they do not automatically predict the optimal solution to a performance problem. In addition, they require a set of specific parameters to be given at the outset, and some adjustments need to be made during the process to solve particular issues (Ben Mosbah et al., 2011).

In the context of meta-heuristics approaches, John Holland (1975) introduces the GA which is an adaptive meta-heuristics imitating the procedure of evolution and natural selection. In 2005, Karaboga started the Bee Colony Algorithm which was founded on the bees' sense for finding food. Also, Glover (1986) introduced the Tabu Search which is a meta-heuristics approach to address combinatorial optimization problems. More clearly, the Tabu Search is a combination of classical local search approaches. In fact, it could be described as the blend of local searches having short-term memories.

Since then, today's transportation network plays a key role in achieving efficiency and effectiveness in SCM and brings significant value to a firm. Crainic et al (2007) emphasize that "intermodal transportation is a relatively new area of research and widely accepted models are lacking in many areas. In such problems efficient resource management and allocation strategies are crucial in order to maximize the utilization of available resources". There exists a number of transportation networks including: direct shipping, cross docking, tailored networks and milk-run (Chopra et al., 2013). According to Wang et al (2009) the milk-run system is more widely applied in automobile industry.

Likely, this is because it is a logistics strategy that supplies products on time and at the appropriate rate thereby optimizing the automobile industry's success. The concept of doing things "just in time" has becoming increasingly popular recently. It is highly correlated to having a good logistics strategy, which in turn plays an important role in the ultimate success of SCM (Sadjadi et al., 2009). The milk run system has been used in the inbound logistics at firms like Toyota, Ford, General Motors and others (Kitamura et al., 2012). In SCM, milk-run is one of the most efficient and regular transportation models (Kitamura et al., 2012). The milk-run is economical when several supplier stations deliver smaller volumes than the truckload. In most cases, it is used internally to deliver raw materials, finished goods to manufacturing plants and warehouses of an enterprise.

The milk-run is defined as "a route on which a truck either delivers goods from a single supplier to multiple retailers or goes from multiple suppliers to a single buyer location" (Chopra et al., 2013). In order to maintain the milk-run pace, firms keep production at a level where their output within a window of time fits with the amount of products received / picked up by each milk-run. As a result, waste relating to inventory in LSC is eliminated and total cost (TC) is minimized. Meanwhile, it speeds up the circulation of materials through facilities which improve the responsiveness of the whole chains (Du et al., 2007). Additionally, the milk-run delivery targets the reduction of transportation costs resulting from the effectiveness of travelling paths and the reduced consumption of fuel (You et al., 2014). It also focuses on promoting efficiency and effectiveness in the procurement of materials. At first, managers calculate the volume of supplies that must meet production plans of subsequent periods. During this stage, potential suppliers are identified in addition to the breaking down of the volume into smaller quantifiable parts. Secondly, the management creates a master milk-run pickup route which accounts for different supplier locations. Thirdly, suppliers are informed about the master route plan to open a platform for delivery of raw material (You et al., 2014). This research concerns the milk-run delivery issue in LSC used by meta-heuristics to predict the optimal network structure, transportation amounts and inventory levels while the objective is to minimize the total cost of the supply chain.

1.3 What is a Supply Chain?

Modern firms are increasingly being compelled to increase their market share in order to meet the growth objectives and survive in the competitive environment. At the same time, the firms must protect their domestic market share from global competitors. Managers are thus confronted with a challenge of how to develop their firms' global logistics and distribution with the intention to fulfill the customer demands in the rapidly changing global supply chain (Handfield, 2002). Handfield states that the strategic positioning of inventories is an important tool towards promoting the prompt availability of products to the customer. Also, Domenica (2003) states that the supply chain ought to be effective and efficient. While its efficiency is measured via the ability to minimize the use of resources to achieve specific outcomes and effectiveness results from the proper design of distribution channels. The specific measures of efficiency in the supply chain are delivery performance, quality of products, the prevalence of backorders and inventory.

Moreover, managers can measure effectiveness using the quality of service and with reference to service needs. Domenica's (2003) parameters suggest that the firm's long-term effectiveness is dependent upon the satisfaction of customer preferences regarding cost, service delivery, quality expectations and flexibility. Thus, all these activities of the SC network are considered a constant challenge for the companies (Ernst, 2002) (show in Figure 1.1). This translates to the design of a more efficient and more effective SC relative to the supply chain adopted by competitors.

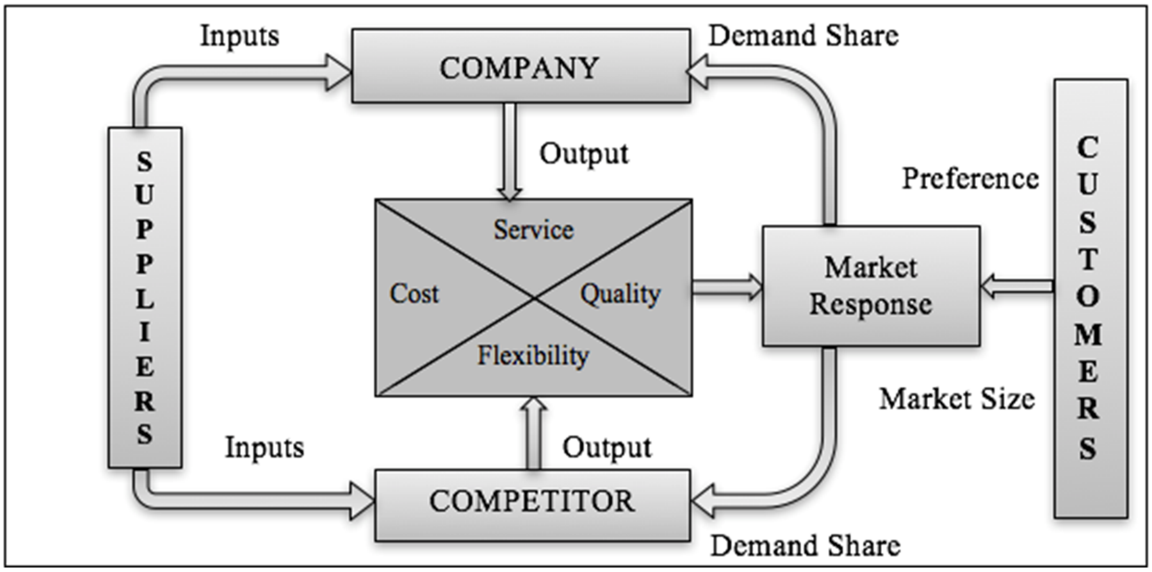

Figure 1.1 Competitive framework in the supply chain
Taken from Ernst (2002)

To optimize the supply chain management, firms must coordinate a number of activities and take many strategic decisions. It therefore requires a cautious management and design of the supply chain. However, firms encounter challenges in the design process arising from the capabilities to assemble assets, skills, competencies and organizations. This is because the design involves work teams, partners, product characteristics and processes.

Mentzer et al (2001) used a combination of ideas from other scholars to stipulate a definition for the supply chain. He argues that the definition of "supply chain" is viewed as the definition of supply chain management. In this case, the SC is a group of three or more than three entities which interact in both an upstream and downstream flow of information, funds, products and services from supply to a customer. It may cover the activities of internal divisions as well as those of external partners such as the suppliers of a manufacturing plant. This implies that supply chains are a series of exchanges between suppliers and customers that take place from the beginning of process until the products reach the ultimate customers. (Handfield, 2002). The Supply chain network is a combination of both an upstream supplier network and downstream distribution channel (Figure 1.2).

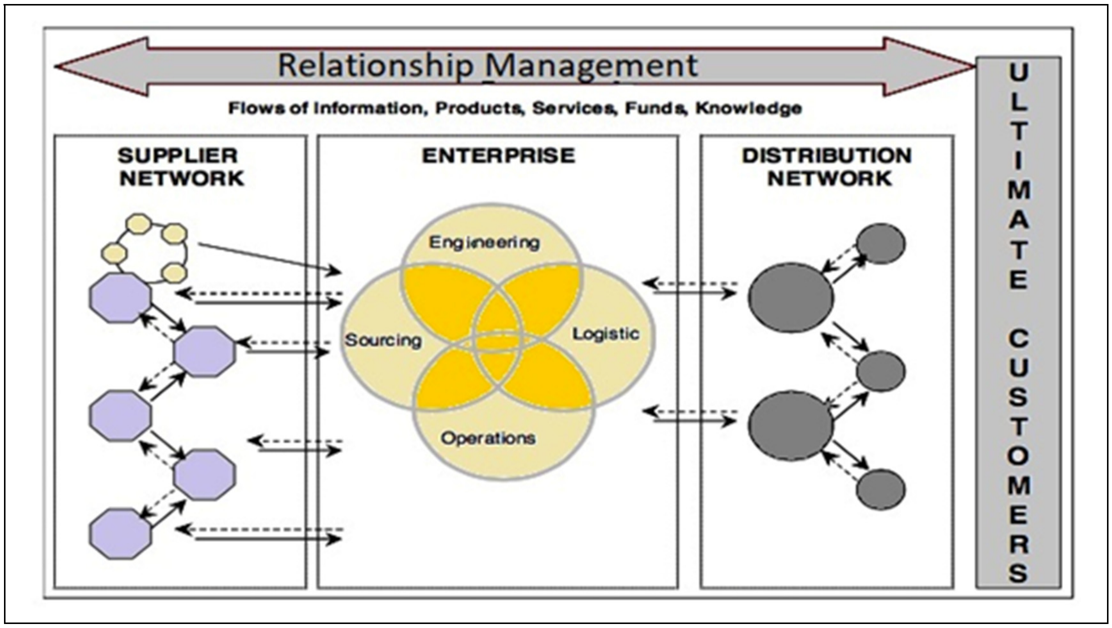

Figure 1.2 Supply chain network
Taken from Handfield (2002)

In other words, the supply chain involves all facilities and activities associated with the flow and transformation of goods from raw materials to the end user and the information flows associated with it. Material and information flow up and down the supply chain. Successful supply chains have to connect different functions within the firm. Therefore, the firms had to satisfy a more informed customer, having far better choices and wanting a wide range of options that provide high value to the end customer. A firm could be part of various of supply chains. Accordingly, increasing attention to the effective interactions, communication channels, and relationships shifted the paradigms of industrial marketing and management giving consistence to the supply chain logic and relational view (Handfield, 2002). In addition, according to Mentzer (2001) defines three types of supply chains depending on complexity of supply chain:

1. The direct SC is composed of the firm, a customer and a supplier.
2. The extended SC consists of suppliers of the immediate supplier and customers of the immediate customer.
3. The ultimate SC includes all the entities involved in an upstream and downstream linkages.

1.4 What Is a Supply Chain Management?

The interpretation of the term ‘supply chain management’ can be quite confusing. In fact, several people use the term in place of logistics to account for the activities of manufacturers, suppliers and customers. Others use it as an umbrella term for purchasing and operations (Tavakkoli-Moghaddam et al., 2006) or the combination of purchasing, operations and logistics (Anand et al., 2008). However, the dynamic business environment of the 21st century has prompted managers and business experts to recognize SCM as the strategic management of supply chain relationships. Most importantly, modern organizations acknowledge that the supply chain is a network of businesses and relationships rather than a chain of businesses. This implies that SCM provides an avenue where organizations can enjoy the benefits of intra- and inter-firm management and integration of supply chain. In this way, SCM targets business processes to promote excellence and offers modern ways of managing relationships within the supply chain.

The global supply chain forum has studied SCM in theory and in practice since it was introduced in 1992. The forum represents a group of non-competing firms and a team of academic researchers tasked with defining the scope and popularizing the concepts of SCM. The group defines SCM as “the integration of key business processes from end-user through original suppliers that provides products, services, and information that add value for customers and other stakeholders’’ (Ma et al., 2012).

Even though the concept of SCM has been studied and analyzed by industrial firms and academia over the last decade, there is not a single definition that is universally accepted to describe it. However, it can be argued that SCM entails the integration of manufacturing, transportation, purchasing, operations and the physical distribution of products into one universal function. This process is characterized by close and beneficial links between various partners who play fundamental roles in the supply chain. They include organizational departments, vendors, third party service providers, carriers and IT service providers. In a general overview, supply chain management encompasses certain core activities such as transportation, procurement, warehouse management, sourcing and inventory control.

Additionally, production planning, scheduling, the processing of orders, forecasting and customer service all point to SCM.

Bolumole (2000) summarized that SCM is a virtually integrated philosophy that manages purchasing and distribution activities within organizations using a definite marketing perspective. On the other hand, Persson (1997) established that SCM was a homogenous concept with the primary objective of boosting the firm’s bottom line. Therefore, SCM has the objective of reducing costs and improving customer service. The cost reduction objective is mainly fulfilled by reducing the levels of inventory held at various facilities. Otherwise, to improve customer service, SCM embraces an end customer focus and coordinates the flow of products to achieve win-win relationships with the customer. Thus, the firms need to integrate their activities with other partners in order to achieve the objectives of SCM through joint effort on customer satisfaction.

The term “supply chain” refers to all the stages involved in fulfilling a customer’s request. These are both direct and indirect and include the manufacturers, suppliers, transporters, warehouses, retailers and even the customers themselves. All the functions related to the supply chain are directed at fulfilling the demands by the customer. For instance, new product development, marketing, operations, distribution, finance, and customer service are all oriented towards customer requests.

According to Chopra et al (2013), SCM refers to the management of the flow between aspects of the supply chain to maximize overall profit. Handfield (2002) defines SCM as the integration of the supply chain organizations by establishing cooperative organizational relationships that promote business processes, flow of information and sustainable competitive advantage. From a different perspective, SCM helps firms to address the threat of increased competition by reducing lead times. This means that the period between acquisition of raw materials and the re-introduction of the finished products to the market is significantly reduced.

In this context, firms with integrated systems of SCM have the upper hand by the virtue of reducing lead times. Similarly, SCM improves a firm’s competitive position by reducing the cost of doing business. In this case, optimized supply management systems save on transport and inventory costs. They also address the problems of vehicle routing and optimize the loading rate. This minimizes fuels costs and prevents the misuse of vehicles. As a result, the firms minimize the expenses that characterize the supply chains.

Therefore, a SCM is defined by all the direct and indirect processes involved in addressing the requests of customers. It is composed of manufacturers and suppliers in addition to transporters, warehouses, retailers and customers themselves. In typical supply chains, information, products and funds constantly flow between the different stages. However, each stage performs different roles but interacts with the other stages of the supply chain. Some prevalent stages in a supply chain include: component / raw material suppliers, manufacturers, wholesalers / distributors, retailers and customers.

It is important to note that the business environment determines the number of stages in a SC. Therefore, some organizations may have more or less stages than others. See Figure 1.3 which shows the different stages of the supply chain management. For example, there some firms that have suppliers, manufacturers, distributers or retailers in their supply chain, but others have suppliers and manufacturers without having a distributer or retailer.

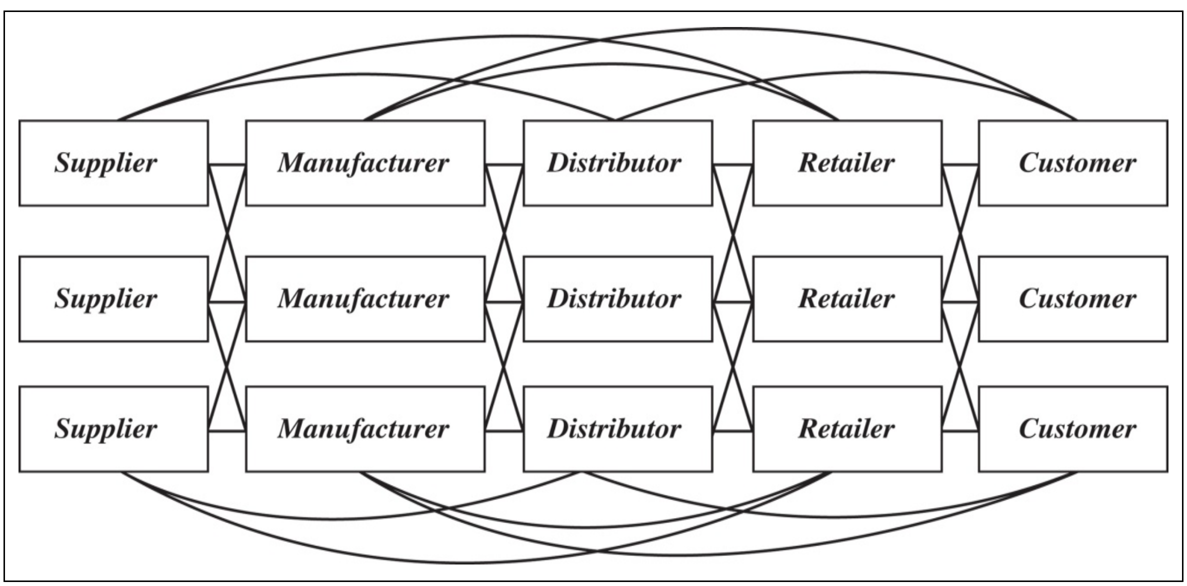

Figure 1.3 Stages of a supply chain management
Taken from Chopra et al. (2013)

For managing the SC more effectively, SC managers usually divide the chain into three operational areas. One is upstream which includes sourcing, purchasing and procurement, negotiating, ordering and inbound transportation and logistics, and collectively it is covered under Suppliers Relationship Management (SRM). The second one in downstream which includes setting up a distribution network, order fulfillment, and out bound transportation and logistics. This comes under the Customers Relationship Management (CRM). The last one is the middle stream, which is inside of the organization and deals with receiving, warehousing, material management, manufacturing scheduling, product development and designing. All these three streams are connected through information technology, which creates a clarity and visibility in the supply chain from one end to another end.

Presently many businesses use SCM as a strategy to have a competitive advantage over others. This is due to cut throat competition. Businesses are becoming more and more customer or market oriented instead of production oriented, so supply chain strategy is the only vehicle suited to satisfy the customers by providing the best quality possible and quick response. Moreover, the objective of every SC is to maximize the overall value created. So, effective SCM is the management of flows among supply chain stages to maximize total supply chain management profits.

1.5 Supply Chain Management Costing

Supply chain management is one of the management tools that deal with the integration of logistics, operational activities, and procurement as well as marketing functions that involves other participants in the supply chain. The Council of Supply Chain Management Professionals defines SCM as the planning and management of all activities involved in procurement, sourcing, conversion, and all logistics management activities (CSCMP, 2014). It is also important to note that SCM incorporates collaboration between the firm and its partners ranging from suppliers and intermediaries to third party service providers and customers. It also includes the supply and demand management within and across firms. There are several costs that are involved in the entire SCM. In some cases, the cost is believed to be comprised of production, distribution, storage and marketability costs. In another case, it is assumed that it is comprised of transportation, operations, and the initial facility cost. However, the total cost of SCM is also believed to entail the production, delivery and inventory cost. The primary focus will be on evaluating the overhead required for the supply chain management.

The production cost refers to the cost that is incurred by any business organization when manufacturing a good or even providing a service. The production costs are comprised of fixed and variable costs. The total amount of the fixed and variables are computed to make up the entire manufacturing costs. Those costs would be accounted for as the products move via the manufacturing processes (Monczka et al., 2015). However, it is possible to calculate the unit production cost from the total fixed and the variable costs. The fixed costs are basically the expenses that do not respond to changes with regard to production output over a certain period of time. These expenses include the building premises rent, depreciation, property taxes, interest payments as well as mortgages. In some cases, the fixed costs go up in a year which can end up increasing the overall fixed cost. For instance, in a situation where the insurance premiums rise upon renewing the policy, the production costs are likely to augment as result of the additional insurance fees (Stadtler, 2015).

The variable costs are the expenses that often change with each production run. From this perspective, direct materials, as well as direct labor, are key components of variable costs. The cost of direct materials is constantly accounted for from the moment that the material leaves the warehouse until the units are completed. On the other hand, the cost of direct labor is broken down and accounted for in terms of the hours that the employee works as well as the pay rate per hour. Thus, the total variable cost is comprised of the total amount of direct labor and the direct material costs (Prajogo et al., 2016). The production costs are involved in setting the fixed cost and estimating the variable costs. In addition, the fixed costs are added to the variable costs and then divided by the number of the units produced to obtain the production cost for one item.

The delivery cost basically involves the logistic costs. Regarding this aspect, the logistic costs include the transportation, storage, labor and administrative costs. In addition, inventory carrying, as well as transportation, add to this expense. However, the logistic costs in most cases depend on the nature of the goods. Aside from that, it is always important to efficiently perform and embrace timely delivery to ensure that the logistic costs are generally low. According to McKinnon (2001), logistical functions account for a large part of SCM costs and they contribute roughly five to ten percent of a firm's total sales. Additionally, Solakivi et al (2012) complete a study on Finnish manufacturing companies and concluded that the costs involved in logistics equalled 12% of firm's annual turnover.

Moreover, there are numerous aspects that may add up and largely affect the logistic costs (Christopher, 2016). They include the fuel costs and delayed arrivals at the ports likely to lead to higher transportation fees. Presence of complex regulations imposed by the government to regulate the international trade. It involves compliance checks as well as document processing. In addition, subsequent delivery delays that can increase the warehousing expenses. There are two main delivery costs of major focus.

The raw material supply costs are often integrated into standard costs when carrying out financial systems. They involve the cost incurred by supplying materials from a single source to the manufacturing plant. However, it is accounted from multiple supplier sources which have different costs depending on where they enter the supply chain. Aside from that the suppliers have different pricing (Coyle et al., 2016).

Overhead for transportation includes the value of assets in transit such as containers and container cars, as well as the cost of product inventory that is incurred in a given move. Aside from that, the cost of assets procured also contribute to transportation tariff.

The inventory costs are the expenditures which are associated with procurement, storage as well as management of inventory. This includes ordering costs, carrying costs and the stock out costs. Ordering costs refer to the charges incurred for procuring inventory. Moreover, it comprises of the cost of purchase and the costs of inbound logistics. The carrying costs is a type of inventory cost. It refers to the costs that are incurred towards inventory storage as well as the maintenance. The inventory storage costs basically involve the infrastructure maintenance preserve inventory and the cost of building rental.

In addition, the cost varies depending on the decision made by the management with regard to managing inventory in-the-house or even through outsourced vendors (Prajogo et al., 2016). The stock out costs refers to the amount of money spent on replenishment. Basically, it indicates the costs incurred in unusual circumstances. They usually form a very small part of the total inventory cost.

1.6 Challenges of Supply Chain Management

Supply chain management is confronted with an organizational flexibility challenge. This entails the adaptability of the firm's mission to maintain the focus on SCM. This means that since SCM is a new concept, firms should rethink their mission statement to include the objectives of SCM and how those objectives may be met. The organizational flexibility determines the success in this ordeal. The performance metrics and decision-making parameters should reflect the goals of SCM. From a different perspective, SCM should enhance the collaboration within the organization and with key supply chain partners to eliminate wastes along the supply chains

Conflicts that arise among partners in the supply chain present a new challenge for SCM. The management of conflicts through mediation is time consuming and sometimes it does not arrive at a solution that is mutually agreed on. This paves way for lawsuits which are usually expensive when they occur. Additionally, the conflicts disorient the supply chains and this affects the continuity of production. Consequently, the firm's reliability decreases in the eyes of the customer.

Firms also encounter difficulties in instilling values, skill and training to partners along the supply chain. This means that the supply chains may not be effective in meeting the needs of the customers. Alternately, the firms have to invest huge sums in training to align with the modern concepts of SCM.

Firms also encounter a lot of uncertainties in SCM. For instance, a supplier may be incapacitated within a planning period causing deficiencies in production and distribution systems. Similarly, the production plant might breakdown due to no fault of the firm. Sometimes there are political or legal changes that cause the suppliers activities to become unlawful and end up inhibiting the firm's activities in general. Similarly, weather changes may affect the transport network which in turn affects the collection and delivery cycles.

Such uncertainties make SCM a complex concept that should be approached with considerable professionalism.

From a different perspective, firms encounter challenges as the attempt to match supply and demand. Sometimes, the market might become volatile in a manner that disables predictions of demand. Additionally, the initiatives taken by competitors may affect the demand of the firm's products. Alternatively, the seasonality of demand means that it is difficult to match it to supply. On the other hand, service firms have a problem in striking a balance between cost and service level. This is because services are intangible and cannot be quantified in the same way that goods are measured. This implies that the costs involved cannot be effectively used to determine the levels of corresponding services. In this light, SCM managers can only use the levels of customer satisfaction as a basis for measuring how the firm meets customer demands.

The product cycles of high technology products are shorter implying that SCM is more complicated. In this case, SCM has to make sure that all the supply chain factors are closely monitored to ensure that customers do not experience shortages. For example, minor delays in the supply of parts results in serious deficiencies in the market that have the potential to deprive firms of customer loyalty.

The varying needs of customers complicate decisions related to SCM. In this case, it is the customer who determines the firm's initiatives as it operates its supply chains. For example, customers may dictate certain shipment methods or carriers that the firm cannot afford.

The Globalization creates a new challenge in the context of SCM. In this case, the geographical distances between various locations around the world increases the transportation costs undertaken in the delivery of goods or supply of raw materials. In addition, globalization complicates inventory management due to higher lead times witnessed in global supply chains.

Chopra and Meindl (2013) describe a supply chain design problem which results from an array of decisions regarding the facility location and the number of production facilities. In addition, managers face a challenge determining the capacities of each production facility.

They also face difficulties in allocating market segments and suppliers for each of the selected locations.

Lastly, SCM strategies tend to vary over time because of seasonality trends and unforeseen competitor strategies. The dynamic business environment of the 21st century implies that firms have to keep adapting their SCM methods. However, abrupt changes disorient the supply chain timelines and schedules. This phenomenon results to inconveniencies within the entire supply chain management.

1.7 Supply Chain Management Characteristics in the Automobile Industry

Automotive manufacturing is considered to be one of the largest industries in the world. Its competitiveness and its dynamism have been scrutinized over the last few decades. According to market-line data from 2014, in 2013 the global automotive industry's overall revenue came to 145 billion EUR with at total production of 144,5 million units recorded. Out of these units, 44.1 percent were passenger cars. Statista (2014) estimated that 72.2 million passenger cars would be sold by the end of 2014. The automotive industry contributes to an average of 3.5 % of the USA's Gross Domestic Product (GDP) (Auto Alliance, 2014). In Europe countries, it contributes approximately 6.9% from GDP (Acea, 2014). Furthermore, they expected that the value of the industry to grow 7.2% annually within the last five years.

In 1913, Henry Ford revolutionized car manufacturing by introducing the assembly line mass production technique. Recently, Toyota has introduced the concept of lean SCM in its Japan production plant making car manufacturing even more efficient (Ohno, 1988). In the early 2000s when Henry Ford's concept of mass production started losing grounds, manufacturing firms began a quest to regain profitability. The initiatives that followed focused primarily on improving the competencies of the supply chain (Holweget et al., 2003). For example, one of the elements that leads to improve competencies of the SC by focusing on reducing the transportation cost. Today efficiency is one of primary aspects in the manufacturing area which has been integrated into the SCM in the name of sustainability (Rebitzer, 2002).

1.8 Automobile Supply Models

Approximately 2000 to 4000 components are used in vehicle manufacture. The parts can differ in color, size, style and demand (Miemczyk et al., 2004). According to Bhatnagar et al (2009), a number of component combinations are witnessed in the automobile industry. For instance, a study on a German car manufacture revealed that out of a daily production of 850 cars, only 15 can depart the manufacturing facility with the similar components.

A relatively large number of suppliers are required to deliver the multiple components to car assembly plants which can be commonly concerned in the automobile industry SC. In addition, exclusive supply methods are used to manipulate the material flow from suppliers as shown in (Figure 1.4). Often, supply methods vary depending on the pickup frequency and transport volume. Physical and geographical factors also play a part (Miemczyk et al., 2004).

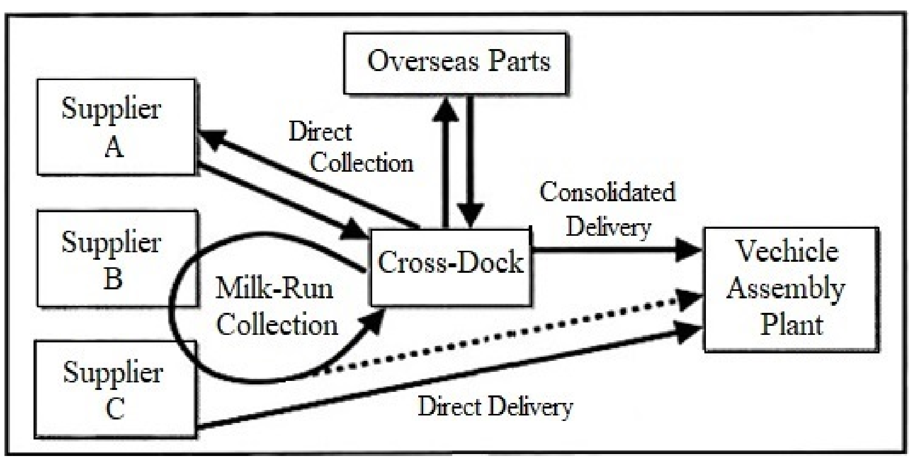

Figure 1.4 Inbound logistics process in the automobile industry
Taken from (Miemczyk et al., 2004)

The use of direct deliveries from supplier to manufacture implies that firms can only receive the components from one supplier at a time. They also represent a rare case of high-volume suppliers. The milk-run collection is the preferred technique where a single truck collects component from more than one supplier locations and delivers them to the manufacturer or the consolidation center using a pre-defined route (Volling et al., 2013). Even though the stoppage incurs costs for each supplier the utilization of the trailer is advantageous because it allows for collections in a single trip. Consolidation at the dock center is where the deliveries are arranged and combined before the final station. This leads to high handling costs as well as high trailer utilization rate. However, direct collection should be arranged in if the supplier is remotely located (Miemczyk et al., 2004). The following table (Table 1.1) shows the advantages and disadvantages between some supply methods.

Table 1.1 Advantages and disadvantages between supply methods

Supply methods	Advantages	Disadvantages
Direct shipping	No intermediate warehouse simple to coordinate	High inventory (due to large lot size
Direct shipping with milk-run	Lower transportation costs for small lots and lower inventories	Increased coordination complexity
All shipments via central DC with cross-dock	Lower transportation cost through consolidation and lower inventory requirement	Increased coordination complexity

Moreover, Miemczyk et al (2004) discussed the transformation in the automobile industry from a push-based supply to pull based supply wherever manufacturing is dictated by the customers' actual demand. The new strategy targets the reduction of finished goods inventory that ties up billions of dollars. However, pull-based supply faces a challenge of long order-to-delivery (OTD) times. This means that SCM managers should strive to reduce OTD lead time though strategies that have already been implemented in the industry (Zhang et al., 2007). One study by Miemczyk et al (2004) found that lean SCM may be a key to having the ability to fulfill the shorter order-to-delivery targets.

CHAPTER 2

OPTIMIZATION WITH META-HEURISTICS APPROACHES

Optimization can be defined as applied mathematics used to gain an accurate and deep intuitive understanding of a system and find possible solutions to the problem. It can also be viewed as part of operational research comprising of areas like modeling, statistics, queuing theory, control theory and production economics. (Lundgren et al., 2010). The following sections will explain basic information on optimization problems, optimization process, meta-heuristics and hybrid meta-heuristics approaches and why they are considered useful for solving the problem in supply chain management optimization which is presented in this thesis.

2.1 Optimization Problem

Recently, optimization strategies have been applied in several economic and technical areas to improve business. They have been used in production planning, transport and logistics, structure design, scheduling of staff and telecommunications (Lundgren et al., 2010). Before that, optimization was first used half a century ago during WWII for military purposes. It then gave rise to the use of strategy in commercial industries (Lundgren et al., 2010). Furthermore, optimization has been used to discover solutions for the following challenges: working within a geographically dispersed complex network, conflicting objectives of different facilities and improving dynamic systems (variation over time, matching demand-supply difficulty, different level of inventory and backorder).

Optimization is defined by Lundgren et al (2010) as “the science of making best decision or making the best possible decision”. In his definition, the “best” indicates an objective function of problem, while “possible” linked to the restrictions of problem. Therefore, a given description of problem is needed to make the best solution or best possible solution for the problem with subject to the prevailing restrictions.

2.2 Optimization Process

The optimization process is typically applied to four stages namely: identify, formulate, evaluate and solve. These stages occur sequentially. The size, structure and complexity of the problem determines the length of time require to complete the process. Figure 2-1 below illustrates how a real-life problem can be solved using the optimization process.

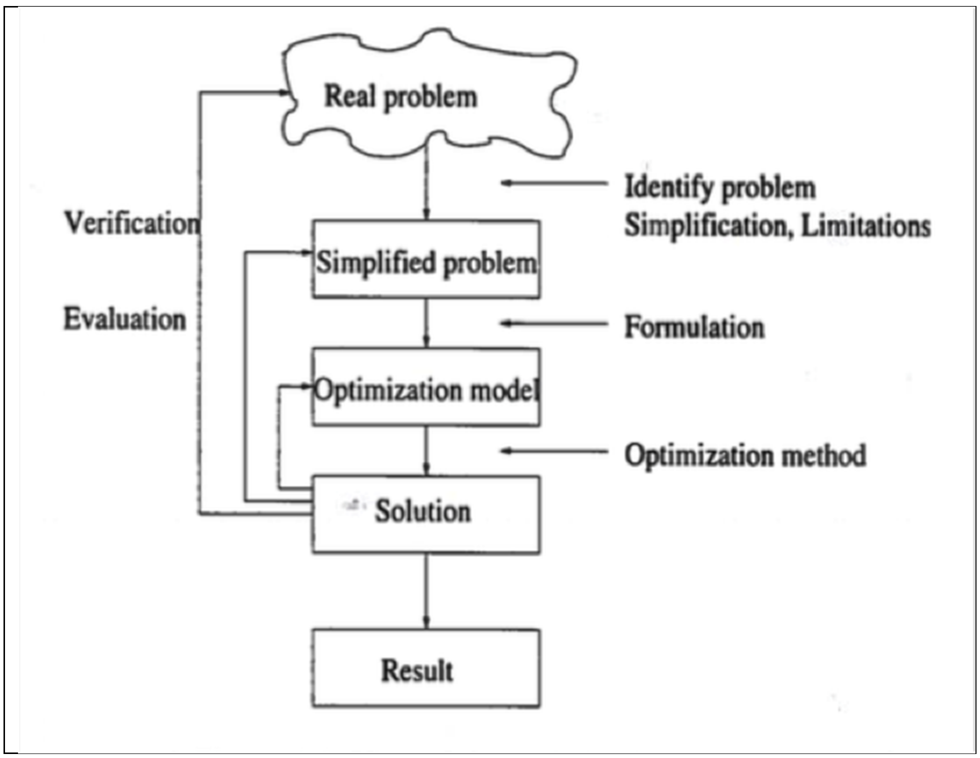

Figure 2.1 Optimization process four stages
Taken from Lundgren et al (2010)

The term "real problem" refers to the actual problem we want to solve. The problem in research is complex and has too many details to model. For solving most problems, it necessary to analyze and simplify them. Then exclude irrelevant elements and do an evaluation. In addition, it is crucial to examine the suitability of the optimization model for a given problem via comparison with existing options. After completing the assessment, the real problem is converted into a simplified form. After this is done, the simplified problem is converted into mathematical form which provides the fundamental characteristics of the problem. In this context, the optimization model contains: decision variables, an objective function and constraints. Therefore, the difficulty of solving problem is based on these factors: complexity, size and structure of the mode.

Optimization problems are grouped into classes depending on the specification of functions and the feasible values for the variables. For instance, an optimization problem can be regarded as a linear programming problem (LP problem), nonlinear problems, integer programming problems and network problems. When all the functions are linear and the decision variables continuous, this problem is called a linear programming problem. However, if a problem has one or more functions which are nonlinear functions, then this problem is a nonlinear programming problem. These kinds of problems are the must difficult to solve by using commercial software (Hillier et al., 2010). The subset of variables for integer programming are non- continuous. The variables are either integers or binary which can only have value as 0 or 1. The network problems can be considered as LP problem or integer programming problems (Lundgen et al., 2010).

The optimization problems are never solved in the best way possible by known methods in an affordable period of time. The computational difficulties faced in solving such problems are frequently due to large dimension, multi extremeness, and inaccurate values of coefficients (Sergienko et al., 2006). Rather, we use meta-heuristics approaches to generate satisfactory solutions to the complex problems (Blum et al., 2003). They are methods used to obtain solutions to complex problems by incorporating both local improvement techniques and higher level strategies to generate a procedure that can escape the local optima and perform a vigorous search of the solution space (Blum et al., 2003). In order to use optimization to solve different problems in different areas such as telecommunication, production planning, transport and logistics, etc.

An optimization problem is the problem of finding the best solution from all feasible solutions. Many optimization problems have been solved by using various meta-heuristics approaches. For example, travelling salesman problem (TSP) is known to be a complex problem because there is no exact solution that can be found in polynomial time. The optimal solution will rarely be obtained in the expected minimal time. For this reason, we usually use meta-heuristics to obtain a good solution. TSP is related to this research problem. Many algorithms were applied to solve TSP with more or less success. The optimization in the TSP is a challenge for a salesperson, who must find the route with the shortest possible distance. The person must start from a certain city, visit each city once, and ultimately return to the city of origin. As a basic index for comparison of various optimization methods, TSP is widely studied. Let C be the matrix of shortest transportation distances (dimension n * n), in which n is the number of cities of graph G. The elements of matrix C represents the shortest transportation distances among all edges of cities (i, j), i, j=1, 2, …, n. The TSP can be formulated within the category programming binary, also known as integer linear programming where variables are equal to 0 or 1, depending on the actual fact whether the route from city i to city j is realized ($x_{ij} = 1$) or not ($x_{ij} = 0$). TSP formulation associates a binary variable x_{ij} with each edge (i, j), equal to 1 if and only if the edge seems in the optimal transportation distance route. Furthermore, C_{ij} is the distance from city i to city j and S is the set of all transportation distances is one route. V is considered the next city. Then formulation of the TSP can be written as the following integer linear programming problem (Dantzig et al., 1954):

$$\text{Min} \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}\, x_{ij} \tag{2.1}$$

and subjected to the constraints which are presented as an example for optimization problem:

$$\sum_{i=1}^{n} X_{ij} = 1, \qquad j = 1,2,\ldots.n, \quad i \neq j, \tag{2.2}$$

$$\sum_{j=1}^{n} X_{ij} = 1, \qquad i = 1,2,\ldots.n, \quad i \neq j, \tag{2.3}$$

$$\sum_{i,j \in S}^{n} X_{ij} \leq |S| - 1, \qquad (S \subset V,\ 2 \leq |S| \leq n - 2) \tag{2.4}$$

$$X_{ij} \in \{0,1\} \tag{2.5}$$

In this formulation, the objective function (2.1) clearly describes the optimal total distance between cities. Constraints (2.2) and (2.3) are constraints that ensure each city visited exactly once. Constraints (2.4) are subtour elimination constraints. Finally, constraints (2.5) impose binary conditions on the variables.

The difficulty involved in obtaining solutions for optimization problems is determined by the complexity, the size and the structure of the model. This means that more simplification can be conducted in this phase. It is also important to consider the amount of data available. In order to use optimization to solve the problems which are often done by implementation of commercial software tools. For this study, MATLAB-2015 has been used. Due to obtain a solution for the model, relevant data must be collected. The data collection stage is critical though challenging due to the pressing need to acquire correct data. Thus, in some cases the data used are approximations instead of the real data and there is a trade-off between exact and more solvable solutions. Therefore, to achieve the result, one has to evaluate and verify the solution in a process known as the post optimality analysis.

However, the generated solution is only for the mathematical model and not necessarily the real problem. Another tool useful in evaluation is sensitivity analysis as it helps determine the most critical parameters of the solution. If changed, the parameters can alter the value of the objective function (Hillier et al., 2010). The evaluated solution is normally used for decision making which leads to the classification of the mathematical model as a decision support tool.

2.3 Meta-heuristics Approaches

The common characteristics of Meta-heuristics approaches include; the use of stochastic components, inspiration by nature, non-reliance on gradient and Hessian matrix of the objective function. They all fit several parameters to the problem. The success of a meta-heuristics approach is determined by its ability to balance between exploration and exploitation. While exploitation identifies parts within the search space that can generate high quality solutions, exploration fosters diversification of the search. One of the first times that meta-heuristics approach was implemented using the Ant System (AS) was with the famous travelling salesman problem in Colorni et al (1992).

The meta-heuristics approaches provide a reliable approach for obtaining optimal solutions to complex and multi-objective problems (Jones et al., 2002). They refer to well-known approaches such as the genetic algorithm, ant colony optimization, tabu search and simulated annealing. The meta-heuristics approaches accept several criteria to determine the non-dominated set by utilizing several alternatives that serve as potential solutions for the multiple objectives (Shanmugam, 2011). According to Shanmugam (2011) meta-heuristics approaches are effective in solving combinatorial optimization problems, their application should follow a well-planned combination of old and new methods that promise the best solution.

2.3.1 Genetic Algorithm (GA)

Genetic Algorithm approach (GA) is a kind of Meta-heuristics approaches that finds the best solution to a certain computational problem to maximize or minimize a function. The GA approach represents one branch of the area of study that is called evolutionary computation. The GA approach provides solutions for complicated non-linear and programming problems (Glover, 1986). The GA follows the natural selection process to perform a randomized search aimed at obtaining optimal solutions to problems. The GA is an approach which relies on the evolutionary paths similar to the ones followed in biological evolution. The choice of solution from an existing set is executed randomly but the probability involved in selection is proportional to the solution's objective functional value. Afterwards, the neighbourhood operators (crossover and mutation) are used upon the chosen solutions. Radhakrishnan (2009) identifies the artificial individual as the basic explanation for the use of genetic algorithm search technique. It has similar characteristics to a natural individual as exhibited by the chromosome and a fitness value. New solutions are obtained by applying crossover and mutation concepts to a starting set of new solutions (Radhakrishnan, 2009).

The GA approach generates a number of solution sets (similar to generations in biological evolution) and tries to advance towards the optimal solution. In this way, it is based on the principles of natural genetic natural selection to find the 'fittest' solutions. The algorithm uses random processes just like evolution. In addition, the user has the capability to change the level of randomization and take control. In executing the genetic algorithm, the user starts with the selection of the current population to generate an intermediate population. Afterwards, the next population is created through the application of mutation and recombination to the intermediate population (Glover 1996). The completion of this cycle constitutes a single generation in the execution process. This approach has an evaluation function which measures performance. The fitness function translates the measured component into an allotment of reproductive opportunities. It works with a number of individuals which represent feasible solutions to the problems being investigated. The individuals are given a fitness score base on the suitability of the solutions. Most importantly, the algorithm only allows highly fit individuals the chance of reproduction via the cross-breeding process (Holland, 1975). New off-springs have desirable characteristics from both parents. This implies that a new population of feasible solutions is created every time those individuals are selected from the existing population and mated. In a matter of generations, good characteristics are obtained. With a well-designed GA approach, an optimal solution can be found (Holland, 1975). The steps of a GA are:

i. Choose initial population

It begins with randomly initial generated states which are satisfactory to the problem.

Example of states:

- N queens
- Each state must have N queens.
- One queen in each column.
- Usually represented by a bit-string or chromosome.

Example: [1 2 3 4 5 6 7 8 9]

ii. Evaluate Fitness function

The fitness function produces the next generation of states by choosing a good fitness to each state. Thus, the probability of being chosen for reproduction is based on the fitness.

iii. Create a new population through

a. Selection

Two parents' chromosomes are selected to reproduce new children. They are selected based on their fitness function. The one with the best fitness has the biggest chance of selection. However, one may be selected more than once where as one may not be selected at all.

Note that there are different techniques, which can be used to choose the best fitness such as roulette wheel, binary tournament, elitist, etc. However, in this thesis, roulette-wheel selection has been applied to pick the best chromosomes' fitness, individuals are assigned a probability of being selected based on current population fitness by:

$$\text{Probability of selection (Pi)} = \frac{\mathrm{Fi}}{\sum_{j=1}^{n} Fi}$$

Roulette-wheel selection is a genetic operator used in genetic algorithms for selecting potentially useful solutions for recombination (Banga et al., 2007).

b. Crossover

For each chromosome to be mated, a crossover point is chosen at random from within the bit-string to create offspring by exchange between parents at crossover point. In this research, order one crossover has been used for permutation-based crossovers with the intention of transmitting information about relative ordering to the off-springs.

Note:

Normal crossover operators tend to produce inadmissible solutions:

- Two chromosomes produce chromosomes offspring.
- There is a chance that the chromosomes of the two chromosomes s are copied unmodified as offspring.
- There is a chance that the chromosomes of the two chromosomes are randomly recombined to form offspring.

Example:

1	2	3	<u>**4**</u>	<u>**5**</u>			1	2	3	<u>**2**</u>	<u>**1**</u>
5	4	3	<u>**2**</u>	<u>**1**</u>			5	4	3	<u>**4**</u>	<u>**5**</u>

Genetic algorithms optimizing the ordering of a given list thus require different crossover operators that will avoid generating invalid solutions such as order one crossover.

Order one crossover: the idea is to preserve the relative order in which elements occur. It works as follows:

- Choose an arbitrary port from the first parent.
- Transfer this part to the child.
- Copy the numbers that are not in the child, from the second parent to the child.

Note:

Start right from the cut point of the part. Then use the order of the second parent and wrap around at the end.

- It is analogous for the second child. The parental roles are reversed.

1	2	3	4	5	6	7	8	9

	4 5 6 7	

9	3	7	2	8	6	5	1	4

Copy rest from second parent in order 1,9, 3,8, 2

1	2	3	4	5	6	7	8	9

3 8 2	4 5 6 7	**1 9**

9	3	7	2	8	6	5	1	4

c. Mutation

Mutation changes some of the bits in the new offspring, which can help to converge faster by getting different solutions. After the change, calculating the fitness must be done again and check. If the fitness is better than before, that means good mutation, else, the mutation should be cancelled.

Example:

1 **3** 2	9 **7** 4 6	5 8

1 **7** 2	9 **3** 4 6	5 8

iv. Replace random / worst ranked part of population with offspring:

Replace the current population with the new population.

v. Evaluate the individual fitness of the offspring:

Test new population whether the end condition is satisfying. If yes, it will stop. If not, it will return the best solution in current population and go back to step 2. The primary advantage of genetic algorithm comes from the crossover operation. Basic GA representation is shown in Figure 2.2 (Banga et al., 2007).

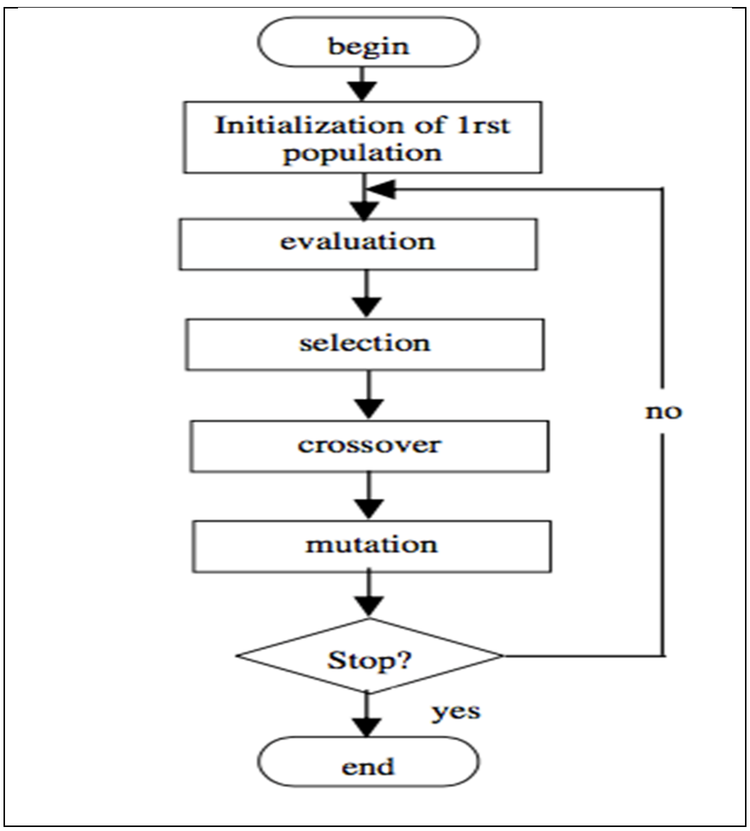

Figure 2.2 Flowchart of basic GA
Taken from Banga et al (2007)

Furthermore, according to (Potvin et al., 1996) the GA approach represents one branch of the area of study that is called evolutionary computation. This is based on the principles of natural genetic and natural selection to obtain fittest solutions. In the same way that evolution works, the GA processes are random and feature factors such as selection, crossover, and mutation. After encoding the solution in an appropriate way, GA works iteratively, evolving to obtain the global optimum. In addition, the participants in a population are motivated to improve their fitness by certain genetic operators. This enhances the generation of global optimum solutions. The following section lists the seven steps of GA (Potvin, et al., 1996):

i. Initiate: Randomly create the initial population of the chromosome.
ii. Evaluate the fitness function: Evaluate the fitness of each chromosome in the population.
iii. Create a new population of chromosomes: Repeat the process of reproduction with the following sub-steps (a, b, c) until an optimal solution that satisfies the optimization criteria is obtained:
    a. Selection: select chromosomes depending on each chromosome's fitness function score. The better a chromosome's fitness, the more likely it is to be chosen. Various techniques can also be used to pick the best chromosomes' fitness, such as a roulette wheel selection.
    b. Crossover: Perform the crossover to produce new chromosomes, which are off springs by exchange between two chromosomes at the crossover point. There are many types of crossovers. In this study, an order one crossover has been used to produce off-springs.
    c. Mutation: After off-springs are produced, perform the mutation, which is the modification of a few randomly chosen genes in off-springs to produce a new off-spring. However, the primary advantage of genetic algorithm comes from the crossover operation.
iv. Re-evaluate the fitness function: Evaluate the fitness of each off-spring that has been produced to find out the best fitness.
v. Replace: Replace the worst random fitness chromosomes of population with off-springs.
vi. Return processes: Repeat processes steps ii to v until the conditions are satisfied.
vii. Stop: Terminate the process.

2.3.2 Ant Colony Optimization (ACO)

Ant colony optimization (ACO) forms a class of recently proposed meta-heuristics for solving complicated optimization issues. Essentially, this approach was inspired by the collective behaviors and trail deposits of ants within their colonies. Ants wander around in large open areas looking for food sources. While exploring paths and searching for food, ants release a chemical component called a “pheromone”. This allows them to find their way back home to the nest after walking about. In order to determine the shortest route between their nest and the food source (Dorigo et al., 2005).

Additionally, the ants from the same colony make a decision on whether to follow their own trails or to take the ones other ants have previously visited.

Since ants can detect each other ants’ pheromone trails, it is possible that an ant will follow another’s path if it contains a high pheromone concentration. Ants following the shortest trail which would be more attractive to other ants that may return to the food source and do a higher number of round trips, so more pheromone is deposited in the trail. At the same time, the pheromone will be less or evaporated over time on other trails (Dorigo et al., 2005). Figure 2.3. depicts how the ants found the most efficient trail between (N) nest and (F) food source. This is an important point to focus on when applying the ant’s behavior to an optimization approach to avoid staying local.

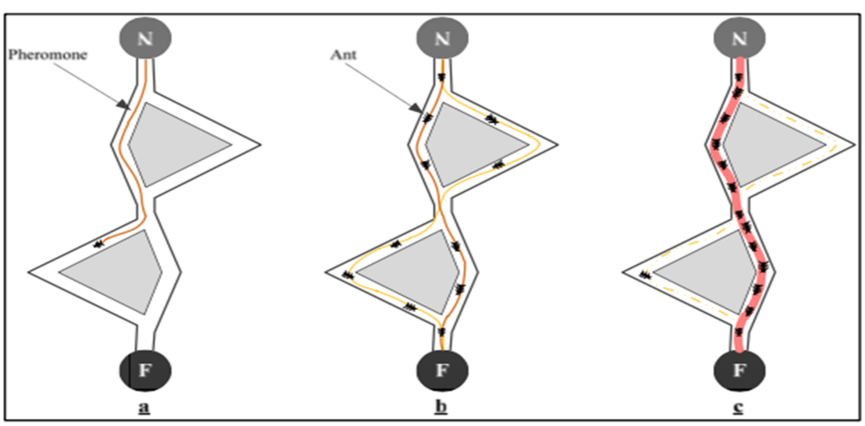

Figure 2.3 Ants needed to find the most efficient trails between the nest (N) and the food source (F). Taken from Dorigo et al (2005)

ACO has various versions which all follow the same idea of solution making with pheromone levels. We can trace its framework as show below (Dorigo et, 2005):

i. Pheromone values are initiated and set to same constant value.

ii. Solution Construction. Each ant begins on a start node and constructively builds a solution based on the pheromone values. A solution is an ordered set of nodes. Ants move from node *i* to node j with transition rule:

$$p_{ij} = \begin{cases} \dfrac{(\mathrm{T}_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{l \in allowed\, N_i} (\mathrm{T}_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}} & if \;\; j \in Ni \\ 0 & Other\ wise \end{cases} \tag{2.6}$$

where

N_i is the neighborhood of node *i*. The neighborhood of node i is the set of all nodes that an ant can move to when at node *i*.

T_{ij} is pheromone values between node i and j.

η_{ij} is a heuristic value.

The values of α and $\boldsymbol{\beta}$ are nonnegative; and they weight the relative importance of the pheromone and heuristic values respectively.

iii. Update Pheromone. The pheromone update is the key difference between most ACO approach; but the general framework still holds. First pheromone is evaporated by this rule:

$$\mathrm{T}_{ij} \leftarrow (1 - p)\, \mathrm{T}_{ij} \;\; \forall (i, j) \in A \tag{2.7}$$

where ρ ∈ (0,1) is the evaporation coefficient.

Then pheromone on some of the paths is increased by:

$$\mathrm{T}_{ij} \leftarrow \mathrm{T}_{ij} + \nabla \mathrm{T}_{ij} \tag{2.8}$$

where the pheromone update, $\nabla \mathrm{T}_{ij}$, is algorithm specific

iv. The solution construction and pheromone update are repeated until the stop condition is met.

In ACO, a computer analogy is implemented to solve various supply chain problems based on the natural movement of ants in search for an optimal distance between their nests and the food source. It is designed to solve a wide range of problems such as salesmen problems, sequential ordering problems and the vehicle routing problem. For the optimization model, the artificial ants travel through a network where they deposit ‘pheromones’ over either the vertices or edges. The initial condition is interpreted as the nest in real ants while the food source is represented by the terminal condition (Dorigoet et al., 2005). The selection of node or vertex for stepping forward is based on a probabilistic model which depends on the quantity of ‘pheromone’ deposited on either the edge or vertex. Additionally, the artificial ants deposit and smell the chemical based on a pheromone matrix (PM). However, the set of constraints that call for the evaluation of each and every selection represents the problem.

2.3.3 Tabu Search (TS)

The tabu search (TS) uses a Local Search (LS) improvement technique to find an optimal solution for combinatory problems. The LS is an iterative search that continuously improves feasible solutions using a series of local moves. An important aspect of the LS is the ‘richness’ of the series of local modifications which affect the quality of solutions obtained. It also uses a basic and direct searching algorithm to optimize complicated problems. It working principle is similar to the human memory which creates a list of the most recent points of investigation (Glover et al., 1997). In this context, the TS also has an important feature known as Tabu. These elements avoid instances of cycling in the course of searching for solutions.

They accomplish this by declaring certain tabu moves which disallow the application of forbidden neighbors. They are found in the tabu list which records a fixed and limited amount of information. In most cases tabu record the neighbors which were not applied in finding a current solution and also prohibit reverse transformations. The creation of this list prevents the possibility of transformation to the points that were investigated on a previous date. At this point, the TS is based on the premise that intelligent problem-solving requires one to incorporate the adaptive memory.

In addition, it is important to note that the tabu list is comprised of certain forbidden moves (Glover and Laguna, 1997). From a different perspective, the use of tabu lists of variable sizes effectively prohibits cycling. This implies that the length of the tabu list should be set based on the problem size. In the course of generating solutions, the length will be increased or decreased in order to attain a better exploration of the search space.

The search space characteristic of the tabu search outlines the possible solutions that characterize a specific search. Each current solution is associated with a definite number of neighborhood solutions. During each iteration, the application defines the probable solution within the search space.

For a problem whose current solution is x, the TS is interested in its neighborhood N(x) which it identifies as x' to meet the condition of a best neighbor (not in the tabu list). There exists subset of neighborhood points known as candidate points which simplify the search. The addition of the new solutions to the tabu list results to the subsequent removal of the oldest member on the list. In this way, it disallows the repetition of moves to prevent the possible entrapment in local minima (Glover et al., 1997).

Additionally, the aspiration and termination criterion acts as an important tool in the use of tabu search as they allow the user to cancel tabu. While the tabu is essential in preventing cycling, they sometimes become too powerful such that desirable moves are prohibited. This can lead to stagnation of the process of searching for solutions. In the most simple, the aspiration criterion allows moves that are in the tabu list provided that the move would result to an objective value that supersedes the current best solution. It provides an avenue where the search can be stopped.

In addition, diversification and intensification allow users to jump to different parts of the search space and to search for solutions with desirable characteristics respectively (Glover et al., 1997). The user can also dictate the search process by discouraging solutions that are likely to be duplicates of other solutions attained at a previous date. This can be applied by imputing certain restrictions on defined attributes that are related to the search history. In this case, frequency and frequency memories aid the exploration of the TS history to impose the said restrictions. The difference between recency and frequency memories can be attributed to the fact that recency memory is short term and is managed through tabu lists while the frequency memory is long term.

In its standard form, the recency memory disallows moves that end up delivering solutions similar to the ones recently visited. On the other hand, the standard form of frequency memory accounts for moves that are disallowed based on the possibility of yielding solutions with attributes that occasionally been shared by solutions obtained in previous searches (Glover et al., 1997). It also encourages solutions with characteristics that seldom occur in previous searches. According to Golden et al (1997), the TS uses an adaptive memory procedure to solve the vehicle routing problem with a min-max objective.

2.3.4 Simulated Annealing

The name of simulated annealing (SA) comes from annealing in metallurgy. Simulated annealing metaheuristic for optimization is typically used when the search space is discrete. The SA approach has been utilized in various domains to solve complex problems, including aerospace engineering, routing, facility layout problems. In these sectors the need for finding an approximate global optimum, is more important than finding a precise local optimum in a reasonable amount of time. (Tavakkoli-Moghaddam et al., 2006). Arnaud et al (2014) utilized SA approach to solve aeroelastic optimization problems. The annealing concept revolves around the heating of solids to high temperatures before cooling them gradually for crystallization to take place. While the heating process excites atoms to move randomly, the cooling process allows the atoms to drop to minimum energy of equilibrium after aligning themselves. The slower the cooling schedule, or rate of decrease, the more likely the algorithm is to find an optimal or near-optimal solution.

Tavakkoli-Moghaddam et al (2006) articulates that SA approach can be used in combinatorial optimizations where the possible solution is represented by the solid state and the energy realized at each state relates to improvements in the objective function. Additionally, the optimal solution in simulated annealing is denoted by the minimum energy.

Furthermore, the SA has been used in hybridizations optimized with another approach to improve the results given by combination with another meta-heuristics approaches such as in a hybrid ant colony and SA algorithm (Sen et al., 2013) or in a hybrid GA and SA algorithm (Zhang et al., 2005).

2.4 Hybrid Meta-heuristics Approaches

The hybrid algorithm uses the meta-heuristics approaches (one or more) together with an optimization / heuristic method that guarantees fast, easier and accurate solutions. Today, most developers are choosing an appropriate combination of several meta-heuristics approaches to achieve more accurate results in solving complex problems.

The hybrids have been extensively implemented and supported by dedicated scientific events such as the workshops on hybrid meta-heuristics. Nevertheless, earlier on, the concept of hybridization of meta-heuristics was not very popular because of the conflicting views of researchers regarding the suitability of individual approaches.

However, it was later recognized that there is not a single optimization approach which is better than others in finding solutions to problems. At this point, the solution to a specific problem was obtained by tuning the algorithm which was sometimes comprised of an appropriate combination of problem specific parts derived from different meta-heuristics. This implies that the key factor in hybridization is the adequate use of problem specific knowledge and combination of the right algorithmic components.

For vehicle routing problems, Potvin et al (1996) suggest that a two-stage hybrid algorithm may be used. They use the simulated annealing algorithm in the first stage to decrease the number of routes before adopting the neighbourhood search in the second step to decrease the costs of travel. Other options include using the genetic algorithm in the first stage together with neural networks in the second and the use of neighborhood search and the genetic algorithm (Potvin et al., 1996). Bres et al (1980) suggest that using the hybrid approach for meta-heuristics such as tabu search and ant colony optimization promises the best results since the method combines the most important features of both.

2.4.1 Hybrid Genetic Algorithm and Ant Colony Optimization (HGA)

GA and ACO algorithms are population-based search algorithms capable of wide applications for solving hard and complex problems across various branches of sciences and engineering. These algorithms can be hybridized with other algorithms (Zukhri et al., 2013). The first ACO was used through focussing on the conduct of real ants (Dorigoet al., 2006). In the ACO algorithm, artificial ants search a graph probabilistically and with the guidance of the pheromone, in order to create candidate solutions. These solutions are then evaluated and used for pheromone updates. Various versions of the ACO have been developed, but they all follow the same idea of solution construction guided by pheromone levels (Qiu et al., 2012).

Many attempts have been made to hybridize these algorithms in order to improve the quality of the solutions. Based on previous studies, the hybrid of genetic algorithm and ant colony optimization (HGA) provides acceptable solutions in a reasonable time (Lee, 2004). This is because several Meta heuristic approaches work together in order to benefit from the best characteristics of each. In view of the foregoing, we propose a hybrid of genetic algorithm and ant colony optimization to solve the milk-run delivery issue in LSC management for AICS.

2.4.2 Hybrid Ant Colony Optimization and Tabu Search (HAT)

In this type of hybridization, the advantages of both the TS and the ACO are utilized in the selection of neighbourhoods. The tabu length strategy in the tabu search works hand in hand with the ant colony optimization to select the neighbourhoods. The pheromone trail in the ACO plays a fundamental role in establishing the most appropriate neighbours that would improve the solution (Eswaramurthy et al., 2008). The significance of ACO can be explained by specific transition rules that guide its application. At the edges of the best generated solution by an ant, more pheromone is deposited by the other ants. During each move, an ant leaves a trail of pheromones behind itself on the connecting path that will be detected by other ants later. As result, following ants choose the next node in this path according to the transition rule, as it has been presented in equation (2.6).

On the other hand, the global updating rule rewards edges that represent the most convenient / shortest path. It modifies the amount of pheromone on the edge that illustrates the shortest path. In this case, the amount of chemical deposited is inversely proportional to the length of path. The ACO also uses the local updating rule to substitute the evaporation phase of the pheromone applied during the construction of the solution.

However, the dynamic tabu length strategy enhances the exploration of the search space. The initial solution is calculated by the Shortest Processing Time (SPT) rule. This SPT rule is considered the time which is spent between all nodes and is represented in the matrix distance. This is improved by the means of the ACO hybridized with the dynamic tabu length strategy. The steps involved in this type of hybridization are:

Initialization

i. Finding tabu length for the current iteration.
ii. Confirming the goal specifications for the neighbors of the current solution.
iii. Establishing the neighbors which are not in tabu.
iv. Updating pheromone value between the operations in the neighbors.
v. Adding a neighbor to the tabu using the state transition rule of ACO.
vi. Finding the current solution.
vii. Applying neighbor from the tabu in the position TP and find the current solution S.
viii. Terminating criterion.
ix. Outputting the solution.

2.5 Supply Chain Management Optimization

2.5.1 Introduction

Currently, optimization is necessary in supply chain management because all parts / members in chain always attempt to optimize their profit through minimizing their cost. Thus, these parts of supply chain may require optimizing. A firm comprehends that processes need to be optimized, if it is not offering its consumers what they want, when they want it while spending little money to achieve it. According to Hasini (2008) SC optimization is essentially a process where resources are used effectively to fill a customer's order, while respecting the limitation within the firm's network and production flow. When focusing on supply chain management, optimization is essential. All SC phases could be viewed as an optimization problem. For instance, minimizing the overall transportation cost while fulfilling consumer's requirements, minimizing inventory holding cost all through the supply chain while fulfilling the demands of end customers or plants. SC optimization is the best opportunity for most firms to significantly their improving overall performance and minimize costs (Ratliff, 2007).

Geunes et al., (2005) characterize SCM optimization as the implementation of optimizing models by a firm in order to manage and enhance their productivity. The optimization of the supply chain aids firms to choose the right strategies and make good decisions in view of the fact that every firm has its distinctive resources, opportunities and limitations. In light of these things it may be said that SCM optimization focuses on developing and maximizing the firms' profits on resources and assets (Bryan et al., 1998). Key supply chain decisions respect transportation, facility location, inventory, and production.

Supply chain management choices could be operational, tactical, and strategic. Choices are activated by both effective supply chain functions and customer requirements. These choices might differ with each other. For example, mass production and customer satisfaction to reduce the manufacturing expense leads to increased inventory levels. In this way, a production level decision has a change for an inventory choice. Conflicting choices need integration and coordination via SC for optimizing the whole processes of supply chain management. Additionally, supply chain advancement is currently driven by consumers, with reduced lead times and augmented consumer expectations. SCM optimization is crucial for a successful customer experience.

Bryan et al (1998) states that SCM and advanced planning schedules are the key fundamentals of supply chain optimization. They add that there are five categories of activities that are associated with the supply chain optimization process. These are: planning, scheduling, executing, tracking and adjusting.

The overall improvement of the SCM that can be expected using optimization approaches can be significant. The accessibility of these approaches opens the way for handling decision-making problem in manufacturing, distribution, and purchasing that could not be sufficiently handled in the past. Currently, supply chain optimization permits manufacturing firms to become extensively flexible and to effectively manage their supply chain through accounting for real life constraints and business regulations. They could re-evaluate hypothetical situations tied to important performance targets that measure their firm's success. They could also create highly optimal plans from the infinite number of possible options they find.

Supply chain optimization and planning calls for a podium that holds the end-to-end supply chain. To be certain, suppliers require getting goods to consumers on time, but they should have the capability of meeting that objective with utmost efficiency at every stride. For the manufacturing enterprise's profit economy, "superior adequate" is never sufficiently adequate. Firms have become adapted to a certain sum of ineptitude, but even little percentage spots of waste convey a price tag that few could afford. The technology and algorithms making up a current optimization solution can aid to close that key gap.

For supply chain optimization to be effective, algorithms ought to intelligently utilize individual issue structure. One of the key differentiators among supply chain optimization technologies is the used algorithms. SCM issues possess special characteristics that must be computed by special algorithms to attain optimum solutions in logical time. For SCM optimization to be effective, people ought to possess the technology and domain expertise needed for supporting the data, models, and optimization engines.

2.5.2 Mathematical Modeling and Optimization

There are numerous studies formulating mathematical model of supply chain through total cost of supply chain (TC). Variables can be defined differently depending on research objectives, but at the strategic level, SC TC model includes some basic elements. According to Tim (2003) SC TC come from Production, Distribution, Storages and Marketability Costs while Sadrnia et al (2013) believe these components are Transportation, Operation and Initial Facility Cost. In the case of available structure and stable market, Zhou et al (2011) assume that SC TC is made up from three elements: Production, Delivery Cost and Inventory Cost.

$$TC = \text{Cost}\,(\text{Production} + \text{Delivery} + \text{Inventory})$$

In this model, sharing analogous point of view with Sunil and Peter, Zhou and Kelin considered distance route (dr) and delivery frequency (n) as decision-making variables while other parameters are designed. As stated by these authors, the theoretical objective function min total cost of supply chain (TC) (equation (2.9)), is generally formulated at operational level as shown by Zhou and Kelin (2011). The production costs of suppliers and manufacture plant include manufacture cost and manufacture start-up cost of parts and finished products cost. The delivery cost is calculated according to the distance route and delivery frequency and it considers the order cost of manufacture plant (which is the transportation cost of parts from suppliers to manufacture plant) and the order cost of customers (which is the transportation cost of finished products from manufacture plant to customers) and it includes also the start-up delivery cost. Meanwhile, the inventory cost is added up from parts inventory cost of suppliers, manufacture plant, in transit and finished product inventory costs of manufacture plant, in-transit and customers. The equation (2.9) in details is as follows:

$$\begin{aligned}
Min\ TC =& \sum_{i=1}^{N}\left\{(UIC_s)_i (SI_s)_i + (UIC_m)_i (SI_m)_i + \frac{(UIC_d)_i P_m dr}{VT} + P_m (UPC_s)_i\right\} \\
&+\sum_{j=1}^{K}\left\{UIC'_m \times SI'_m + (UIC'_c)_j (SI'_c)_j + \frac{(UIC'_d)_j (D_c)_j\, dr}{VT} + (D_c)_j (UPC_m)\right\} \\
&+\left(\sum_{i=1}^{W}\{(USC_s)_i + (FOC)_i\} + \sum_{j=1}^{K}\{USC_m + (FOC')_j\} + FDC + UDC \times dr\right) n \\
&+\left(\sum_{i=1}^{N}\left\{(UIC_s)_i P_m\left(1 - \frac{P_m}{2(P_s)_i}\right) + \frac{(UIC_m)_i P_m}{2}\right\} + \sum_{j=1}^{K}\left\{UIC'_m\left((D_c)_j - \frac{((D_c)_j)^2}{2P_m}\right) + \frac{(UIC'_c)_j (D_c)_j}{2}\right\}\right) \Bigg/ n
\end{aligned} \tag{2.9}$$

In addition, from this modelling of supply chain management (equation (2.9)), the total cost of supply chain has been simplified to a shorter form as shown below in equation (2.10) (Nguyen et al., 2015):

$$Min\ TC = A*dr + B*n + C*n*dr + D/n + E \tag{2.10}$$

where:

$$A = \sum_{i=1}^{N}\left(\frac{(UIC_d)_i P_m}{VT}\right) + \sum_{j=1}^{K}\left(\frac{(UIC'_d)_j (D_c)_j}{VT}\right)$$

$$B = \sum_{i=1}^{N} \left\{ \left(USC_s\right)_i + \left(FOC\right)_i \right\} + \sum_{j=1}^{K} \left\{ USC_m + \left(FOC'\right)_j \right\} + FDC$$

$$C = UDC$$

$$D = \sum_{i=1}^{N} \left\{ \left(UIC_s\right)_i P_m \left(1 - \frac{P_m}{2\left(P_s\right)_i}\right) + \frac{\left(UIC_m\right)_i P_m}{2} \right\} + \sum_{j=1}^{K} \left\{ UIC'_m \left(\left(D_c\right)_j - \frac{\left(\left(D_c\right)_j\right)^2}{2P_m} \right) + \frac{\left(UIC'_c\right)_j \left(D_c\right)_j}{2} \right\}$$

$$E = \sum_{i=1}^{N} \left\{ \left(UIC_s\right)_i \left(SI_s\right)_i + \left(UIC_m\right)_i \left(SI_m\right)_i + P_m \left(UPC_s\right)_i \right\} + \sum_{j=1}^{K} \left\{ \left(UIC'_m\right) SI'_m + \left(UIC'_C\right)_j \left(SI'_c\right)_j + \left(D_c\right)_j \left(UPC_m\right) \right\}$$

Therefore, the above equations for A, B, C, D and E have been formulated to obtain the equation (2.11) of the optimal delivery frequency (n) (Nguyen et al., 2015):

$$n = \sqrt{\frac{D}{B + C * dr}} \tag{2.11}$$

2.5.3 Optimization Objective

The main objective here is to minimize the transport distance between the facilities, which can be modelled as the sum of the distances to all the facility locations in just one route. In this integer linear programming problem, d_{ij} is considered the distance between two facilities in the distance route (dr) while F is the number of facilities in supply chain.

$$Minimize\ dr = \sum_{i=1}^{F} \sum_{j=1}^{F} d_{ij} x_{ij} \tag{2.12}$$

2.5.4 Constraints

1- Ensure that each customer / supplier is serviced / supplied only once and included in one route:

$$x = \begin{cases} 1 \text{ if vehicle travels from i to j} \\ 0 \text{ otherwise} \end{cases} \tag{2.13}$$

2- Ensure that a route is fully connected and that there is no sub-route:

$$\sum_{i,j \in \mathrm{F}} X_{ij} \leq |\mathrm{K}| - 1, \quad (\mathrm{K} \subset \mathrm{i}, \;\; 2 \leq |\mathrm{K}| \leq \mathrm{F} - 2) \tag{2.14}$$

where

K is the set of all transportation distances in one route

F is number of facilities in supply chain.

3- Ensure that the vehicle starts and ends at the same facility. As shown below, [1] means facility number 1, which is both the start and the end of the same route:

Route = [1]: [F+1]

However, the path from the second facility [2] to the last facility [F] is random:

Random route= [2]: [F]

4- Respect the vehicle capacity which is maximum load of 20 tons.

Lastly, this chapter describes the meta-heuristics and the hybrid meta-heuristics approaches which can be useful to solve / find possible solutions for optimization problem. Also, it presents the mathematical modeling that will apply to an automobile industry problem in following chapter.

CHAPTER 3

SUPPLY CHAIN MANAGEMENT OPTIMIZATION USING HYBRID META-HEURISTICS FOR AN AUTOMOBILE INDUSTRY CASE STUDY

This chapter is focused on studying modeling meta-heuristics and hybrid meta-heuristics approaches and their potential in regard to cost reduction in the automobile industry which can be defined as applied mathematics used to gain an accurate and deep intuitive understanding of a system and find possible solutions to the problem. The following sections present examines modeling genetic algorithm (GA) and hybrid genetic algorithm (GA) with ant colony optimization approaches (ACO) meta-heuristics approaches for the problematic of the automobile industry and results of testing both (GA) and (HGA). Then, obtained solutions will be discussed as well as express the conclusions and propose future work.

3.1 Modeling Meta-Heuristics Approaches for Automobile Industry Case Study (AICS)

3.1.1 The Problematic of the Automobile Industry Case Study (AICS)

In this automobile industry problem, we consider a supply chain network with nine facilities, including one manufacturing plant facility (1), three suppliers (2,3,4) and five customers (5, 6, 7, 8, 9) as shown in Figure 3.1. Thus, this automobile industry supply chain is considered as small case study because it has less than 15 facilities. Additionally, the milk-run system has been used to delivery of goods from manufacturers to suppliers or customers. The purchasing and distribution are integrated into the same delivery route. The purchasing and distribution are consolidated in order to reduce delivery cost. The delivery cost is calculated according to the frequency and distance and including delivery start-up cost and mileage cost. Also, manufacturing plant, suppliers and customers each hold a certain percentage of safety stock and besides that the number that has been set in transit.

In this case, classical optimization methods may be unable to find optimal solutions for such small case which is considered as an integer linear programming problem with nonlinear constraints. Additionally, there are 9! solutions which are approximately 20,160 possible route solutions, which makes this problem complicated. For these reasons, this problem is complicated. Thus, meta-heuristics approaches are good to find near or optimal solution because almost all metaheuristic approaches tend to be suitable for global optimization.

Consequently, to optimize the supply chain, we need to consider the transportation distance delivery model to minimize the transportation cost between the manufacturing plant, the suppliers and the customers by going to each facility only one visit. The objective of this problem is to minimize the total cost (TC) of the supply chain by applying the following strategy: the shortest delivery route (dr) and the optimal delivery frequency (n). This strategy will have a significant impact on the level of stock and the quantity of goods with regard to the manufacturing plant, suppliers and customers. The optimization problem is defined by the parameters to be adjusted and the objective to be optimized. We will apply both the genetic algorithm approach as well as the hybrid of the genetic algorithm and ant colony optimization approach to study their advantages and disadvantages compared to each other and to the ACO approach, using the same data from AICS and applying the same TC function (Equation 2.9) developed by Zhou and Kelin (2011).

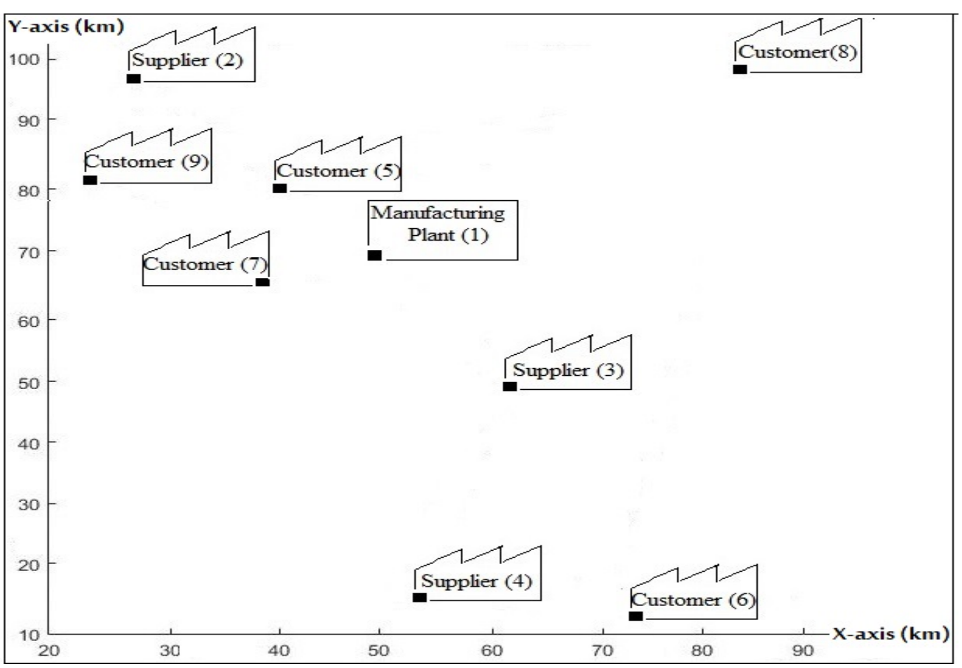

Figure 3.1 Geographical location of AICS facilities

3.1.2 Specific Data of the Automobile Industry Case Study (AICS)

In this automotive industry case study, a production cycle is set up for (T) 30 days. The physical location of each AICS facility is noted in Table 3.1 and the unit of linear distance is equal to 1km. A truck with a maximum load of 20 tons is used to complete the delivery task. The start-up delivery cost is 1000 at a time which is fixed cost, and the unit deliver cost is 5 $ per km. The speed of the delivery (v) is 50 km/h.

Table 3.1 Geographical location of AICS facilities

Facility / Location	1	2	3	4	5	6	7	8	9
X-axis (km)	50	26	62	52	40	73	38	86	21
Y-axis (km)	70	95	49	15	80	12	66	97	82

The supply chain values of the AICS are given in Table 3.2 and Table 3.3. Later, this data will be utilized as input data for Equation (2.9). The SC in an AICS has single manufacturing plant facility. This is identified as facility number 1, because the route will always start and end here. Facilities 2, 3, and 4 are considered as suppliers, while facilities 5, 6, 7, 8 and 9 play the role of customers as listed in Table 3.3. Due to use the ton unit of measure, Table 3.4 illustrates the total weight of delivery quantity for customers and supplier facilities of AICS.

Table 3.2 Data of manufacturing plant and supplier facilities for AICS

Facilities / locations	1	2	3	4
$UPC_{m/s}$	50	10	12	15
$USC_{m/s}$	5000	1000	1500	2000
$UIC_{m/s}$	10, 12, 15	10	12	15
UIC_d	-	12	14	18
$SI_{m/s}$	4000	4000	5000	8000
SI'_m	16 000	-	-	-
UIC'_m	50	-	-	-
FOC	-	100	100	100
W(kg)	-	2	1.5	1.5
W'(kg)	5	-	-	-
$P_{m/s}$	126 000	134 000	135 000	138 000

Table 3.3 Data of customer facilities for AICS

Facilities / process	5	6	7	8	9
FOC'	200	200	200	200	200
UIC'_c	50	50	50	50	50
UIC'_d	60	60	60	60	60
SI'_c	2200	2000	1800	2000	1800
D_c	22 000	20 000	18 000	20 000	18 000

Table 3.4 Data of total weight of delivery quantity for customers and supplier facilities of AICS

Facility	2	3	4	5	6	7	8	9
Delivery Quantity	134 000	135 000	138 000	22 000	20 000	18 000	20 000	18 000
Unit weight(kg)	2	1.5	1.5	5	5	5	5	5
Total weight(kg)	268 000	202 500	207 000	110 000	100 000	90 000	100 000	90 000
Total weight (ton)	268	202.5	207	110	100	90	100	90

3.1.3 Implementation of the Proposed Genetic Algorithm (GA)

Genetic Algorithm is proposed to find the best solution for the shortest route in a logistics network of automobile industry supply chain. There are approximately 20,160 possible route solutions, which makes this problem complicated. In addition, this case study is considered as an integer linear programming problem with nonlinear constraints. In this study, the steps defined by Potvin et al (1996) have been used as illustrated in Figure 3.2. GA is first applied on data from the transportation distance matrix d_{ij} of AICS, as shown in Table 3.5. Each facility is given a unique integer value index from facility number 1 to facility number 9 and every chromosome is designed to represent a solution for the problem, keeping in mind that the route must not repeat facilities. The length of the chromosome, which is one delivery route (dr), is selected to be equal to the number of facilities of AICS.

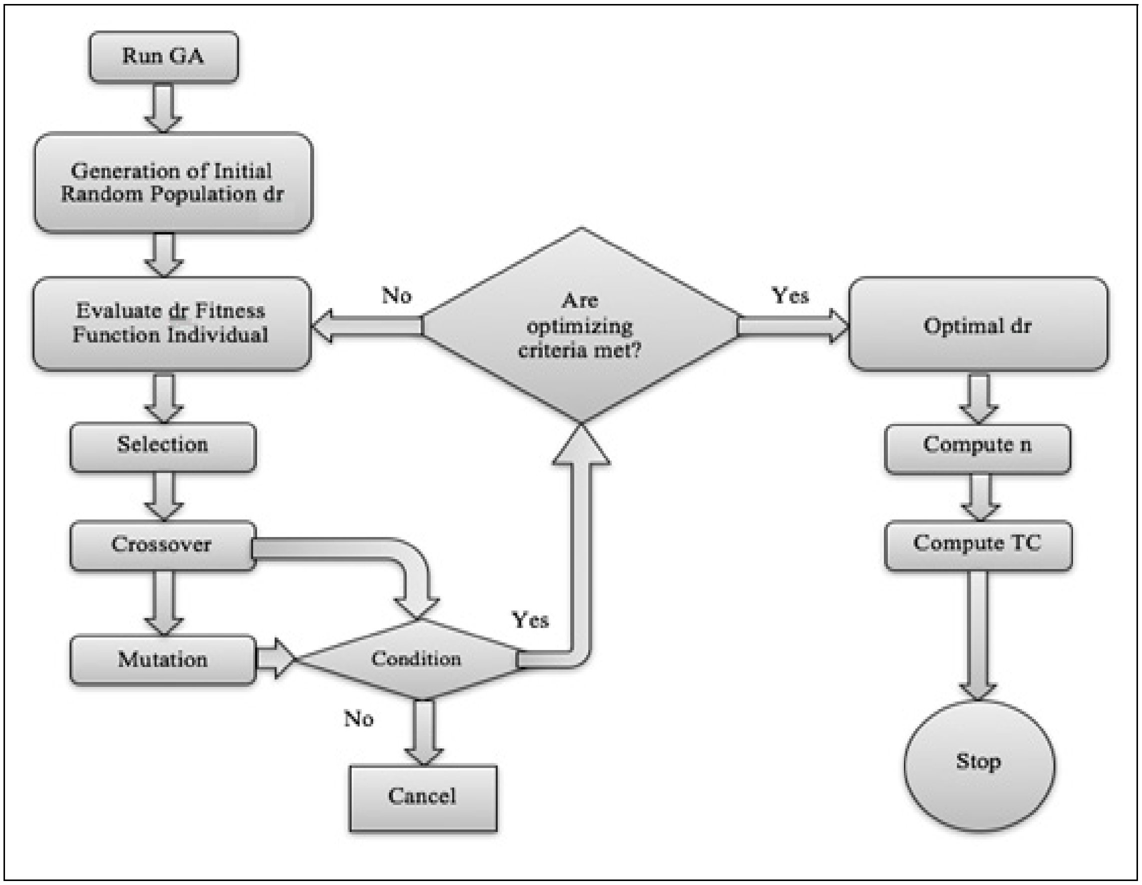

Figure 3.2 Flow chart of proposed GA for optimizing route distance (dr)

Encoding, permutation encoding can be used in ordering problems and it can also be used in this problem. In permutation encoding, every chromosome is a string of numbers that randomly represents the number of facilities. The number of facilities in each chromosome is fixed. From AICS data, as mentioned previously, there are nine facilities: a single manufacturing plant, three suppliers and five customers. The optimal dr is calculated from (1, 2, 3, …, F, 1). Different routes are based on the same geographical location of facilities (Table 3.1) with different transportation distances between locations from i to j which is transportation distance matrix d_{ij} among facilities of AICS, calculated by using a symmetric problem formula defined by Equation (3.1) and its result is presented in (Table 3.5):

$$d_{ij} = \sum \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \tag{3.1}$$

Table 3.5 Transportation distance matrix d among facilities of AICS

$d_{ij}=$

0.00	34.66	24.19	55.04	14.14	62.39	12.65	45.00	31.38
34.66	0.00	58.41	84.12	20.52	95.38	31.38	60.03	13.93
24.19	58.41	0.00	35.44	38.01	38.60	29.41	53.67	52.63
55.04	84.12	35.44	0.00	66.10	21.21	52.89	88.77	73.82
14.14	20.52	38.01	66.10	0.00	75.58	14.14	49.04	19.10
62.39	95.38	38.60	21.21	75.58	0.00	64.35	85.99	87.20
12.65	31.38	29.41	52.89	14.14	64.35	0.00	57.14	23.35
45.00	60.03	53.67	88.77	49.04	85.99	57.14	0.00	66.71
31.38	13.93	52.63	73.82	19.10	87.20	23.35	66.71	0.00

Identification of the optimal dr:

The optimal dr is obtained by the following steps, which have been adapted for this study. They are illustrated in Figure 3.2:

1) Find all possible route solutions (F-1)! / 2 where F=9 is the number of facilities.
2) Set random permutation for (9-1)! / 2 that contains the number of all different facilities.
3) Choose 9 random chromosomes (routes) as the initial population from the data of transportation distance matrix d of AICS.
4) Check the validity of the routes (all facilities ≠ 0, no sub-route).
5) Compute fitness function (optimal route dr) for each route with Equation (2.12).
6) Select the best 4 chromosomes (routes) by roulette wheel selection. The selection is based on current population fitness (dr value) by probability of selection (Rao, 2009).
7) Randomly create 2 off-spring populations from 4 existing chromosomes (routes) by applying an order one crossover operator. In this case, each group of 2 chromosomes (routes) produces one off-spring. Two crossover points will be chosen randomly from the third gene (facilities) and seventh gene (facilities) for the first chromosome. This part

is then transferred to the off-spring (new route). After that, the genes (facilities) which are not in the off-spring are copied from the second chromosome (route) to the off-spring (new route). This last step is done by starting from the right of the cut point of the part of the first chromosome (route) and by using the order of the second chromosome (route), which is wrapped around at the end.

8) Mutate randomly by choosing 2 genes (facilities) in the off-spring and by switching them. However, if the new off-spring (new route) value is bigger than the old off-spring (old route), the mutation is cancelled.
9) Compare the 2 off-springs (new route value dr) with the old chromosome (old route dr).
10) Continue to check other possible values of the route until the optimization criteria are reached which happens when all successive GA iterations no longer produce better results compared to the initial population.
11) Stop when the near optimal or optimal dr is found.

After, GA checks all possible dr to identify the optimal dr which then used to identify the optimal delivery frequency (n) by equation (2.11). Afterwards, the optimal (dr) is computed as well as the delivery frequency (n), can obtain the total cost of the supply chain (TC) by using the obtained values of (dr) and (n) in following equation previously mentioned in chapter 2 in equation (2.10).

$$\text{Min TC} = 1000*(11220+7.616dr+11.8n+11\,798.853 / n) +5dr*n$$

$$A=\sum_{i=1}^{3}\left(\frac{(UIC_d)_i\ 126\,000}{50*30}\right)+\sum_{j=1}^{5}\left(\frac{(UIC'_d)_j\ (D_c)_j}{50*30}\right) = 7616$$

$$B=\sum_{i=1}^{3}\{(USC_s)_i+(FOC)_i\}+\sum_{j=1}^{5}\{5000+(FOC')_j\}+1000 = 11\,800$$

$$C = 5$$

$$D=\sum_{i=1}^{3}\{(UIC_s)_i\ 126\,000\left(1-\frac{126\,000}{2(P_s)_i}\right)+\frac{(UIC_m)_i(126\,000)}{2}\}+\sum_{j=1}^{5}\{50((D_c)_j-\frac{((D_c)_j)^2}{2*126\,000})+\frac{(UIC'_c)_j\ (D_c)_j}{2}\} = 11\,798\,853$$

$$E = \sum_{i=1}^{3}\{ (UIC_s)_i\ (SI_s)_i + (UIC_m)_i(SI_m)_i\ +\ 126\,000(UPC_S)_i\} + \sum_{j=1}^{5}\{ (50)(16\,000) + (UIC'_c)_j(SI'_c)_j\ +\ (D_c)_j\ 50\} = 11\,220\,000$$

3.1.4 Implementation of the Proposed Hybrid Genetic Algorithm and Ant Colony Optimization (HGA)

Hybrids of genetic algorithm and ant colony optimization are used to obtain the best result in terms of the optimal route (dr) by using transportation distance matrix d of AICS as shown in Table 3.5. In the ACO approach, artificial ants probabilistically search a graph, with the guidance of pheromone, in order to create candidate solutions. Candidate solutions are then evaluated (dr) and pheromone updates repeated until the stop condition is met by choosing only the first 9 iterations. This number of iterations has been chosen in relation to the number of the facilities in this AICS. This can be achieved by following a temporary memory or tabu list before being selected as the initial population for GA approach. The alternative is selecting random initial population and then following the stages as in the previous GA approach, including identifying optimal n and TC. The framework is used as guide to find the optimal delivery route (dr) for hybrid genetic algorithm and ant colony optimization. All the codes were written and implemented in MATLAB-2015. The main steps of the codes can be found in Appendix 2.

1) Set the parameters and assign the initial pheromone value on each path to the same constant value.
   - Heuristic exponential $\beta = 1$
   - Pheromone exponential $\alpha = 1$
   - Constant value $Q = 1$
   - Number of ants (population size) $M = 9$
   - Evaporation rate $E = 0.05$

Note:

α controls the relative importance of the pheromone trails

β is a parameter which determines the relative importance of pheromone versus distance.

2) Solution Construction. Each ant begins at a start facility and first ants move can be chosen randomly next facility. During each move, an ant leaves a trail of pheromones behind itself on the connecting path that will be detected by other ants later on to calculate the transition probabilities. Thus, ants constructively build a solution based on the pheromone values. Ants choose to move from the facility (i) to facility (j) based on a probabilistic decision P_{ij}^{m}, and then onto a facility that has not yet been visited, as shown in Equation (3.2) (Dorigo et al., 2006):

$$P_{ij}^{M} = \begin{cases} \dfrac{(\mathrm{T}_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}}{\sum_{s \in allowed\, m_i} (\mathrm{T}_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta}} & if \quad j \in \quad allowed\, mi \\ 0 & Other\ wise \end{cases} \tag{3.2}$$

where:

m_i is the feasible neighborhood of facility (i). The neighborhood of facility (i) is the set of all facilities that an ant can move to when at facility (i).

T_{ij} is the pheromone value between facility i and j.

η_{ij} is a heuristic value, $\eta_{ij} = 1 / d_{ij}$, where dij is the distance of move from facility i to the facility j.

3) The update pheromone. Once all ants have finished constructing their routes, the pheromone trails are updated. A constant evaporation factor is used to lower the pheromone trail and then ants are allowed to deposit pheromone on the transportation distance they have visited.

4) The construction of solution and pheromone update is repeated until the stop condition is met by the selected first 9 iterations.

5) The best four chromosomes (routes) are then selected by roulette wheel the from first 9 iterations of ACO, becoming the initial population for GA and then following the same stages as the previous GA approach, including identifying optimal n and TC.

In summary, after checks all possible dr to identify the optimal dr. Afterwards, the delivery frequency (n) is computed by equation (2.11) as well as the total cost of the supply chain (TC) with equation (2.10).

3.2 Results

In this thesis, meta-heuristics solution approaches have been proposed for lean supply chain management problem in the automobile industry. As it can be seen from the results, the genetic algorithm is starting from the facility 1. It does a full array formula cross of other facilities to find the optimal value dr. A hundred tests had been done with MATLAB-2015 in order to obtain the near or optimal dr (see Appendix 1) with both the GA and the HGA approaches. For each test, the number of iterations has been recorded as well as the near or optimal dr (km). Then, for each approach, the mean value and the standard deviation have been calculated for the number of iterations and for the value of dr. For ease of comparison, the minimum and maximum values have been identified with colors in the table of Appendix 1.

For the Genetic Algorithm approach (see Appendix 1), the number of iterations varies from 3 to 36 with an average of 21.1 ± 7.5. The near or optimal dr varies from 283.30 km to 326.36 km with an average of 290.9 ± 8.0 km. The best value of optimal dr obtained is then 283.30 km and is illustrated in Figure 3.3. It is important to underline the fact that this best optimal dr was obtained only 21 times over the 100 tests.

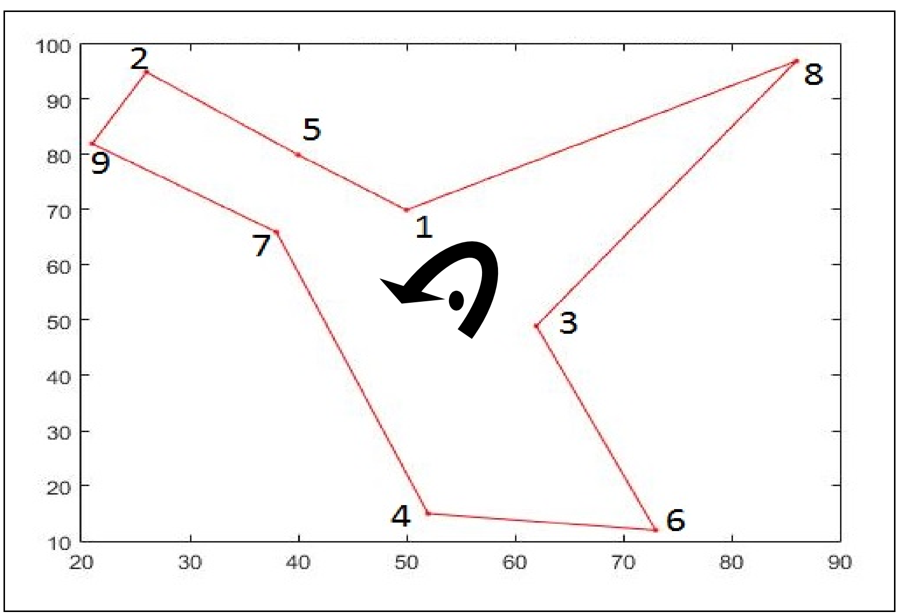

Figure 3.3 Optimal dr (283.30 km) with GA

This optimal delivery route goes in all the facilities, in this order: 1-5-2-9-7-4-6-3-8-1, as presented in Table 3.6. However, this optimal route dr does not respect the criterion for the vehicle capacity of 20 tons. The weight carried by the delivery truck will vary during its route: it will increase when picking up goods from a supplier and it will decrease when it delivers goods to a customer. It is thus possible to calculate the actual weight of the truck for each stop in its route. According to this optimal dr (283.30 km), the total weight for the pick-up goods from suppliers equals to: 8.93 + 6.9 + 6.75 = 22.58 tons (see Table 3.6). This value exceeds the criterion for the capacity of the vehicle. Thus, all these goods cannot be carried in one route. In other words, the 9 facilities of the LSC of this AICS cannot share this sole milk-run and it must be divided into two sub-routes.

Table 3.6 Optimal dr from GA and HGA

Approach	dr (km)	Optimal delivery route
GA	283.30	1 – 5 – 2 – 9 – 7 – 4 – 6 – 3 – 8 – 1
Delivery weight 1 time/day	22.58 Tons	-3.66 + 8.93 - 3 - 3 + 6.9- 3.33 + 6.75 - 3.33
HGA	283.30	1 – 5 – 2 – 9 – 7 – 4 – 6 – 3 – 8 – 1
Delivery weight 1 time/day	22.58 Tons	-3.66 + 8.93 - 3 - 3 + 6.9- 3.33 + 6.75 - 3.33

Therefore, the new optimal dr that is for delivery and for pick-up goods becomes longer than the total of transport distance between facilities, while the value of n remains unchanged as calculated by equation (2.11). In addition, the sub-routes of new optimal dr are as follows: (dr1) is 1-8-3-6-4-7-1 and (dr2) is 1-9-2-5-1(see Figure 3.4 and Table 3.7). With these two new sub-routes, the capacity of 20 tons has been respected since the maximum weight was 13.65 tons. With these sub-routes, the new optimal dr equals to 295.94 km. Once this optimal dr has been obtained, we can calculate the delivery frequency (n) by equations (2.11) and then minimize the total cost of the supply chain (TC) by the equations (2.10). The result shows that the delivery frequency is equal to 30 deliveries / month for both dr1 and dr2. Thus, the total cost of the supply chain is found to be equal to 14,265,635.58 $ (see Table 3.7).

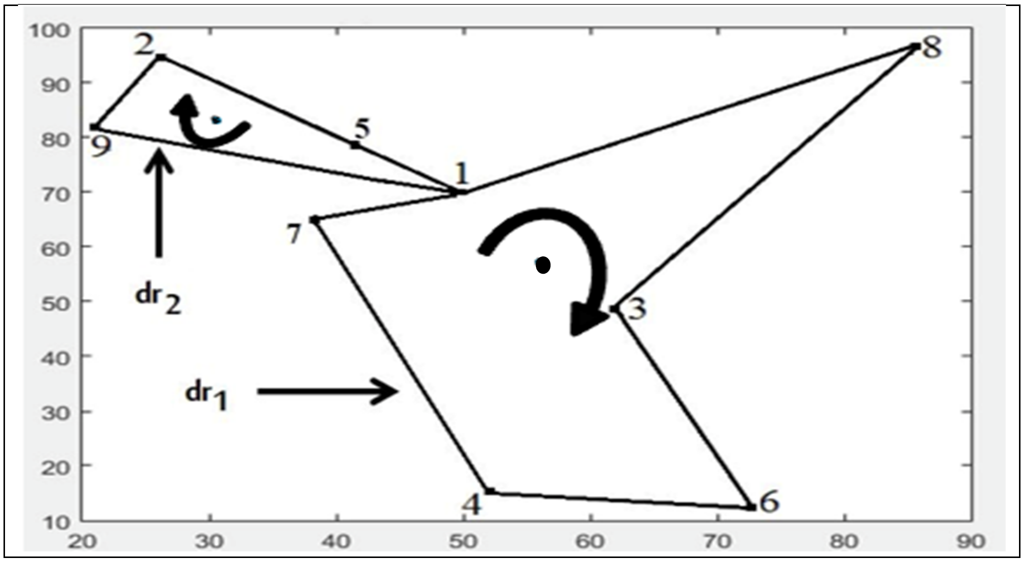

Figure 3.4 Optimal delivery sub-route dr1, dr2 (295.94 km) with HGA

Table 3.7 Optimal dr with two sub-routes found from GA and HGA

Approach	dr (km)	Optimal delivery sub-routes	n	TC ($)	Note
GA	295.94	dr_1 :1 – 8 – 3 – 6 – 4 –7 – 1	30	14 265 636.58	Optimal TC
		dr_2 :1 – 9 – 2 – 5 – 1	30		
Delivery weight 1 time/day	13.65 Tons	dr_1: -3.33 + 6.75 - 3.33 + 6.9 -3			
	12.59 Tons	dr_2 : -3 + 8.93 - 3.66			
HGA	295.94	dr_1 :1 – 8 – 3 – 6 – 4 –7 – 1	30	14 265 636.58	Optimal TC less iterations
		dr_2 :1 – 9 – 2 – 5 – 1	30		
Delivery weight 1 time/day	13.65 Tons	dr_1: -3.33 + 6.75 - 3.33 + 6.9 -3			
	12.59 Tons	dr_2 : -3 + 8.93 - 3.66			

The same results have been obtained for the hybrid genetic algorithm and ant colony optimization approach (see Appendix 1). For the HGA, the number of iterations varies from 10 to 30 with an average of 20.4 ± 5.2. The near or optimal dr varies from 283.30 km to 308.47 km with an average of 287.9 ± 5.2 km. The best value of optimal dr obtained is then 283.30 km and is illustrated in Figure 3.5. It is important to underline the fact that this best optimal dr was obtained only 38 times over the 100 tests.

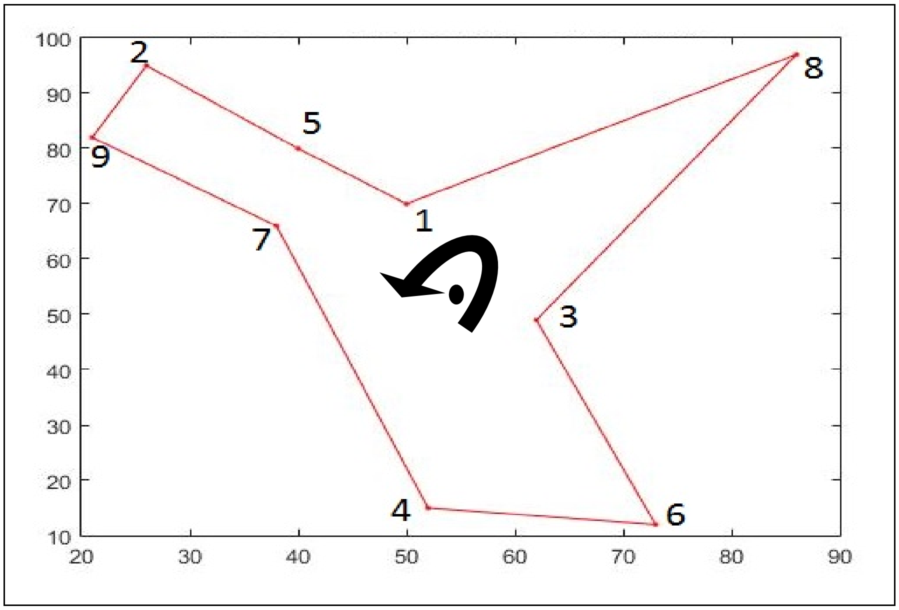

Figure 3.5 Optimal dr (283.30 km) with HGA

Once again, this optimal route dr obtained with HGA does not meet vehicle capacity by delivering all the facilities in one delivery route distance, so it is divided into two sub-routes distances which are the same as those obtained from GA and are presented in Table 3.7.

If the results for GA and HGA are compared, the average numbers of iterations seem very similar. However, if this average number of iterations is calculated only from the 21 tests for GA and the 38 tests for HGA, both for the best value optimal dr, these averages become: 28.6 ± 4.9 for GA and 21.5 ± 5.0 for HGA (see Appendix 1: last line of the table). The proposed HGA approach has been proven to be slightly better computational efficient than the GA approach. HGA has obtained the same optimal dr (283.30 km) (Figure 3.5) but this optimal value of dr was obtained with a lower number of iterations between 10 to 30. Additionally, this approach has achieved the optimal dr 38 times out of 100 tests compared to GA which achieved the same optimal dr with more iterations, between 18 to 36, only 21 times out of 100 tests. In addition, the average of near or optimal dr results of the HGA (287.5 ± 5.2), is very slightly better than from the average of near or optimal dr result of the GA (290.9 ± 8.0). In summary, HGA is slightly better than GA (see Appendix 1).

3.3 Discussion of the Results

The review of related work has led us to the following comparison between meta-heuristics approaches.

The automobile industry case study (AICS) was studied by Zhou et al (2011). They built up a theoretical total cost (TC) model for the milk-run delivery issue in LSC by considering the three factors that most influence the total cost of supply chain: production, delivery and inventory costs. Hence, they developed an equation to minimize TC. They then solved it by applying the improved ant colony optimization (ACO). Later, Nguyen et al (2015) worked on the same case study but with different meta-heuristics approaches: mixed integer programming (MIP), along with a hybrid of ant colony optimization (ACO) and tabu search (HAT). They wanted to compare different meta-heuristics approaches.

They compared their results with those of the original ACO. All these previous results including those of the present study can be found in Table 3.8. Nguyen et al (2015) found that the MIP results outperformed the previously obtained ACO results as well as the HAT results. Thus, MIP can minimize the total cost of an entire supply chain of the AICS. The AICS involves only a few facilities (less than 15) making it a small-scale LSC, so the results indicated that the use of MIP is pertinent in a small-scale LSC.

However, MIP, HAT and ACO were also tested with random data in large-size LSC (Nguyen et al., 2015). The results showed that MIP encounters significant difficulties in such cases. When the number of facilities is greater than 15, the time spent in finding the optimal dr makes MIP all but useless as an industrial application (Nguyen et al., 2015). In fact, compared with ACO and HAT, MIP requires a very long processing time when handling a large-scale LSC. When random data were tested 100 times, optimal dr from the HAT was superior to ACO in most cases (Nguyen et al., 2015).

Table 3.8 Optimal dr with two sub-routes found from ACO, MIP, HAT, GA and HGA

Approach	dr (km)	Optimal delivery sub-routes	n	TC ($)	Note
ACO	301.75	dr1: 1 – 5 – 9 – 2 – 8 – 1	19	15 766 546.00	
		dr2: 1 – 7 – 4 – 6 – 3 – 1	19		
MIP	295.94	dr1: 1 – 8 – 3 – 6 – 4 – 7 – 1	30	14 265 636.58	Optimal TC
		dr2: 1 – 9 – 2 – 5 – 1	30		
HAT	301.75	dr1: 1 – 7 – 5 – 9 – 2 – 1	30	14 268 360.90	
		dr2: 1 – 8 – 6 – 4 – 3 – 1	30		
GA	295.94	dr1: 1 – 8 – 3 – 6 – 4 –7 – 1	30	14 265 636.58	Optimal TC
		dr2: 1 – 9 – 2 – 5 – 1	30		
HGA	295.94	dr1: 1 – 8 – 3 – 6 – 4 – 7 – 1	30	14 265 636.58	Optimal TC, less iterations
		dr2: 1 – 9 – 2 – 5 – 1	30		

These different kinds of meta-heuristics approaches have ability to help optimizing the entire SCM. However, based on this research, it was found that not all meta-heuristics approaches have the same efficiency and effectiveness. In this study, the obtained results show that the HGA is slightly better efficient compared to the GA and another meta-heuristics approach for solving milk-run delivery issue in lean supply chain management. In addition, HGA and GA have obtained the same optimal dr (283.30 km) like the one obtained with MIP but HGA can be considered slightly better when compared to other existing meta-heuristics by getting the best optimal route (dr) with fewer iterations than GA and less computing time. The advantage of the HGA approach has over the GA approach is that it provides better average results from a comparatively slightly smaller number of iterations. It is able to find an acceptable solution in a relatively short amount of time so it looks ideal for solving optimization problems occurring in practical applications. Furthermore, the modelling and optimization of supply chain has been an important research subject to provide better optimal solutions which are much needed to increase overall supply chain management profit. Furthermore, this work can be further extended to solve large-scale LSC case using other meta-heuristics approaches.

CONCLUSION AND RECOMMENDATIONS

In general, it could be concluded that the supply chain management optimization versus lean supply chain management is used to improve the performance among the various facilities / echelons in particular of supply chain and the whole system. Also, supply chain coordination in all stages of the supply chain occur simultaneously which usually results in greater total supply chain profits. The success of supply chain management highly depends on the timely and efficient production / distribution in the supply chain network, to be more effective, responsive and flexible. Meanwhile, the SCM seeks to gain a competitive advantage through minimizing cost and providing high quality and service for the end user. Aside from that, the computing time is an important aspect to consider in modeling as it is a decision support tool for the supply chain management optimization. The firms must often make the decisions relatively fast and must therefore have a model and methods that can provide an optimal or near optimal solution within in a reasonable amount of time. Better solution is needed within short amounts of time due to the scarcity of resources.

This thesis introduces the genetic algorithm approach (GA) as well as the hybrid of genetic algorithm with the ant colony optimization (HGA) approach which have been applied to optimize the total cost of one lean automobile industry supply chain. In particular, by minimizing delivery, production and inventory costs through controlling the flow of materials / products between supply chain facilities of the AICS, from one manufacturing plant to multi suppliers and multi customers. This refers to an optimal milk-run delivery which finds the shortest distance at the lowest cost. Through the case analysis results, we can conclude that when the milk-run model is applied to the automobile industry it improves the load factors, shortens the delivery distance, increases the time efficiency, and fulfills the transport demands and minimizes the transportation cost in the entire supply chain of automobile industry.

In fact, the results from this research confirm that milk-run optimization issue of supply chain management can be obtained by applying meta-heuristics approaches as well as hybrid meta-heuristics approaches. These results show that the genetic algorithm approach (GA) along with the hybrid of genetic algorithm and ant colony optimization approach (HGA) for the design of a logistic distribution network in supply chain of the automobile industry are effective in achieving an optimal solution for shorten transport distance into the milk-run delivery within reasonable amount of time. Meanwhile, it can avoid the delay of materials and enhance the accurate transportation. In addition, based on the obtained results, the genetic algorithm and the hybrid of genetic algorithm and ant colony optimization approaches have superior performance when compared to the ant colony optimization (ACO) to obtain optimal or near optimal solution for the automobile industry supply chain. Furthermore, the hybrid of genetic algorithm and ant colony optimization gives good results that can be obtained by using less iterations and computing time than the genetic algorithm approach itself. As results, this can lead faster to an optimal solution and this has been proved in automobile industry case study. Consequently, the hybrid of genetic algorithm and ant colony optimization approach seems quite promising for industrial applications.

Moreover, the work in this thesis has covered a small-scale problem in the SCM optimization but there are still several research directions for future work as the large-scale problem. In addition, since GA and HGA are superior to ACO, these approaches give new space for practitioners and researchers. This means that meta-heuristics approaches / hybrid meta-heuristics approaches can be utilized for efficient solutions. However, they would first have to be applied in larger-scale problems to confirm this trend. Furthermore, the work can be further extended to solve this problem using other hybrid meta-heuristics. Also, it needs to be extended to other industries and service. Full implementation of the supply chain management optimization and lean in the supply chain will provide additional benefits to all. Thus, it is significant to encourage firms to embrace full implementation of lean in their supply chains management by extending the research to different levels in supply chain facilities like suppliers, manufactures, distributors and end customers. Research case studies to compare the findings in this thesis with practices in industry will help to further align this research to industry requirements. Also, more use of the case study research method based on illustrative evidence and predictive research using modeling (mathematical and modeling) will assist to verify claims about the benefits of the supply chain management optimization.

APPENDIX 1

Table of Results of Testing GA and HGA

GA Results		
Tests	Number of iterations	Near or Optimal dr (km)
1	21	286.69
2	19	288.37
3	29	283.30
4	19	297.03
5	23	288.37
6	36	283.30
7	27	293.54
8	25	286.22
9	23	286.92
10	9	305.68
11	5	300.72
12	28	283.30
13	8	326.36
14	13	307.16
15	14	302.71
16	22	283.30
17	20	286.31
18	16	293.89
19	30	283.30
20	28	293.54
21	21	286.68
22	27	283.30
23	21	286.22
24	29	283.30
25	16	295.74
26	19	286.68
27	20	286.22
28	27	283.30
29	25	293.54
30	29	286.68
31	16	295.74

HGA Results		
Tests	Number of iterations	Near or Optimal dr (km)
1	22	283.30
2	29	288.98
3	18	283.30
4	19	289.92
5	30	283.30
6	13	286.22
7	15	283.30
8	25	283.30
9	23	286.92
10	20	292.41
11	13	283.30
12	23	288.98
13	12	288.71
14	30	283.30
15	16	293.54
16	26	283.30
17	17	286.31
18	16	293.89
19	24	288.22
20	21	283.30
21	18	286.68
22	16	293.54
23	21	283.30
24	28	283.30
25	16	295.74
26	19	286.69
27	20	286.22
28	27	283.30
29	25	293.54
30	29	283.30
31	16	295.74

32	29	283.30
33	21	286.68
34	19	286.68
35	16	295.74
36	32	283.30
37	27	293.54
38	29	283.30
39	27	293.54
40	16	295.74
41	26	287.99
42	29	283.30
43	19	286.68
44	29	298.87
45	22	293.54
46	26	283.30
47	11	305.68
48	9	307.16
49	29	283.30
50	19	286.68
51	21	294.62
52	20	288.71
53	35	287.99
54	21	286.22
55	19	286.68
56	3	310.29
57	27	283.30
58	9	293.54
59	22	292.19
60	18	292.25
61	19	294.77
62	34	283.30
63	23	292.57
64	13	286.31
65	18	298.36
66	36	283.30
67	21	295.01
68	19	283.30
69	26	283.30
70	19	296.09
71	13	287.99
72	33	286.68
73	9	286.31
74	13	286.31

32	28	283.30
33	21	286.68
34	19	286.22
35	16	283.30
36	13	286.22
37	15	283.30
38	18	283.30
39	23	286.92
40	20	292.41
41	13	288.98
42	25	283.30
43	12	288.71
44	29	286.22
45	13	286.22
46	26	283.30
47	13	298.88
48	20	283.30
49	23	286.31
50	19	283.30
51	21	283.30
52	22	288.98
53	19	283.30
54	14	308.47
55	14	305.87
56	23	286.22
57	28	288.98
58	22	288.98
59	21	283.30
60	19	287.99
61	17	293.54
62	23	286.31
63	21	283.30
64	13	292.41
65	26	286.68
66	13	293.54
67	27	286.68
68	24	283.30
69	18	283.30
70	22	287.99
71	15	286.31
72	16	283.30
73	26	292.93
74	23	283.30

75	20	292.93		75	10	294.52
76	24	297.37		76	11	283.30
77	27	293.54		77	26	286.22
78	11	294.62		78	15	283.30
79	22	288.71		79	26	286.68
80	19	288.98		80	11	305.68
81	28	286.22		81	21	288.37
82	22	296.09		82	28	283.30
83	18	292.25		83	21	294.62
84	16	288.37		84	26	288.37
85	18	293.54		85	28	283.30
86	27	293.54		86	18	292.57
87	36	283.30		87	23	283.30
88	29	286.22		88	27	289.92
89	20	289.92		89	25	283.30
90	23	286.31		90	30	283.30
91	6	318.21		91	22	286.22
92	17	286.31		92	18	287.99
93	12	304.75		93	17	286.31
94	25	289.92		94	23	288.71
95	30	283.30		95	24	283.30
96	4	302.42		96	22	283.30
97	18	283.30		97	18	292.57
98	12	288.37		98	19	286.22
99	14	289.09		99	20	283.30
100	25	286.68		100	12	286.22
Average ± st. d.	21.1 ± 7.5	290.9 ± 8.0			20.4± 5.3	287.5 ± 5.2
Average ± st. d. (Good dr Value)	28.6 ± 4.9	283.3			21.5 ± 5.0	283.3

The minimum value has been identified with YELLOW.
The maximum values have been identified with RED.
The shortest route has been identified with GREEN.

APPENDIX 2

Code for Hybrid of Genetic Algorithm with the Ant Colony Optimization Approach (HGA)

The main steps of the codes for HGA are as follows:

- **<u>Solution Construction</u>**

```
for it=1:9
Move Ants
  for k=1:nAnt
    ant(k).Tour=randi([1 facilities]);
    for l=2:facilities
    i=ant(k).Tour(end);
    P=T(i,:).^alpha.*hv(i,:).^bhv;
    P(ant(k).Tour)=0;
    P=P/sum(P);
    r=rand;
    C=cumsum(P);
    j=find(r<=C,1,'first');
    ant(k).Tour=[ant(k).Tour j];
end
```

- **<u>Calculate dr</u>**

```
Tour=ant(k).Tour;
sum1=0;
A_1=0;
B_1=0;
for g=1:9
     A_1=Tour(g);
     if(g<9)
          B_1=Tour(g+1);
     else
           B_1=Tour(1);
     end
         sum1=sum1+D(A_1,B_1);
     end
     ant(k).dr=sum1;
     if ant(k).dr<Best.dr
         Best.dr=ant(k).dr;            % Store Best dr
         f=it;                         % Store iteration of Best dr
     end
end
```

- **Update Pheromones**

```
For k=1:nAnt
tour=ant(k).Tour;
tour=[tour tour(1)];
   for l=1:facilities
    i=tour(l);
    j=tour(l+1);
    T(i,j)=T(i,j)+Q/ant(k).dr;
    end
 end
 Results(it,:)= tour(:)
 Evaporation
 T=(1-rho)*T;
 Store Best Cost
 BestCost(it)=Best.dr
 Show Iteration Information
 Bestiteraion=f
end
```

- **Crossover**
- **Test crossover process**
- **Mutation**
- **Replace the current population with the new population.**

```
xx=0;
yy=0;
dr=0;
p=0;
min=dr_fit_ness(1,10);
for i=2:9
    if(dr_fit_ness(i,10)<min)
        min=dr_fit_ness(i,10);
        p=i;
   end
end
dr=min;
dr
p
if p==0
    for i=1:9
        mm=dr_fit_ness(1,i);
        xx(i)=x(mm);
        yy(i)=y(mm);
    end
 else
    for i=1:9
        mm=dr_fit_ness(p,i);
        xx(i)=x(mm);
        yy(i)=y(mm);
```

```
    end
end
        xx(10)=xx(1);
        yy(10)=yy(1);
```

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