ASSESSMENT OF INVENTORY AND TRANSPORTATION COLLABORATION IN A LOGISTICS MARKETPLACE

by

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Declaration of Authorship

I declare that this (project/thesis/dissertation) is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

To my friends and family . . .

Abstract

The globalization of businesses and the consequent competition introduce significant pressures on logistics systems. One such key demand on the role of logistics within organizations is the increased emphasis on time-based competition, i.e. the speedy manufacture, delivery to markets and the servicing required, as a result of increasing dependence on the ability of organizations rapidly and efficiently to deliver customer-adapted products worldwide. The growing need for transparent, flexible, and easily adjustable logistics services has fostered the creation of digital brokerage platforms that match a variety of logistics demands with supply, widely known as an Electronic Logistics Marketplace (ELM). In this thesis, a comparative study was conducted for three distribution strategies with different levels of inventory collaboration. The Multi-Depot Vehicle Routing Problem (MDVRP) with supply and demand constraints were formulated for each strategy, and the mathematical models thus created were tested using random datasets generated on varied levels of customer dispersion. It was determined that the model representing the strategy of full inventory and distribution collaboration resulted in the least cost in all cases with an average savings of 76.70% as compared to the model with no collaboration. Since General Algebraic Modeling System (GAMS) was limited to small-sized problems for the models, an adaptation of the Variable Neighborhood Search (VNS) metaheuristic was developed and coded using C++ programming language. The heuristic was tested on several datasets, and had a deviation of 2% - 8% from the optimal solutions. The algorithm was further analyzed by testing larger sets, and it returned solutions for 90 nodes within 3200 seconds. Furthermore, a sensitivity analysis was conducted to assess the effect of changing some key input parameters on the total logistics costs. The input parameters were changed one at a time in a one-way sensitivity analysis study, and the effect of parameters' variation on the total logistics cost was observed. Overall, the most influential inputs are the number of customer nodes, error in forecasted demand, last-mile cost per km, and vehicle capacity.

Keywords: ***inventory collaboration, logistics marketplace, multi-depot VRP, optimization, routing***

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List of Abbreviations

3PL	Third-Party Logistics
AVL	Automatic Vehicle Location
CTM	Collaborative Transportation Management
ELM	Electronics Logistics Marketplace
GAMS	General Algebraic Modeling System
ICT	Information Communciation Technologies
LCP	Lane-Covering Problem
LTL	Less-than Truckload shipping
MDVRP	Multi-depot Vehicle Routing Problem
SMC	Secure Multiparty Computation
TL	Truckload shipping
UCC	Urban Consolidation Centers

Chapter 1. Introduction

1.1. Background

Most companies start out with a single distribution point, whether they manufacture/assemble their product within or outside the region. Therefore, this single distribution point is a drop-ship location, meaning that these retailers ship directly from that facility [1]. Depending on the growth of the company, the distribution point will shift to a single warehouse for effective distribution, mainly because small businesses need to limit their expenditures while wanting to maintain flexibility as their growth rate has high levels of ambiguity at this stage [2,3]. From a single distribution point of view, a business is stumbled upon two alternatives to grow further. Firstly, the company could outsource and charge the consumer shipping, which often on a per unit basis can be very high [4]. This would be a significant cost to the consumer and therefore a higher overall cost of the product compared to other options. The second option would be for the business to subsidize these expenses themselves [3]. This would again not be a feasible choice, especially for small companies. Therefore, the only real alternative would be to spatially spread their distribution points to effectively decrease the overall logistics costs incurred by the company [5]. This is the traditional growth path for a supply-chain logistics network; however, it comes with a significant challenge. Increasing the number of distribution points translates to a huge escalation in investment of real estate, labor and equipment across the network [6]. The only other option is to be confined with long-term fixed cost commitments by signing up with the necessary third-party service providers [7].

1.1.1. Current challenges with inventory and transportation in a traditional logistics network. According to the latest Annual State of Logistics Report, total logistics activity in the U.S. in 2016 cost $1.39 trillion, which is a 1.5% drop in overall logistic cost from last year, despite the rise in energy prices [8]. This indicates that energy prices are no longer the primary factor in logistic cost. According to the report, consumer trends are the new driving forces of logistic spending, which is visible by the powerful impact of rising consumer demand for e-commerce deliveries [9].

A few noticeable trends include overcapacity over various logistic sectors fueling increased concentration and efficiencies to sectors such as warehousing, parcel delivery and motor freight [4]. Moreover, warehouses and parcel carriers are capitalizing on the growing e-commerce volume by increasing their rates and continuously reconfiguring their networks to meet the rising consumer expectations for faster delivery [10].

Although inventory storage alone accounts for about 10% of total logistics cost, it has a substantial effect on the overall cost of transportation. A more distributed network reduces the enormous outbound shipping costs, however, with an increase in inbound transportation costs [11]. Regardless, with the development of e-commerce businesses, significant challenges arise in terms of customer expectations in comparison to traditional retail. Since the business model requires outbound shipping of very small quantities directly to individual customers, the shipping time itself becomes a critical factor [8]. The giant retailers in the market such as Amazon have optimized their supply chain such that they can offer same-day delivery at reasonable prices, creating a new benchmark for customer expectations that is almost impossible to match [11]. In addition, the product demand in an e-commerce can be highly unpredictable due to several other factors such as social media trends and their impact on customer demand [12, 13].

Moreover, the sheer acceleration of e-commerce growth presents its own set of challenges on the logistics industry. In 2017, total ecommerce sales worldwide was around $2.3 trillion, and is expected to hit $4.5 trillion by 2021, according to the Enterprise Guide to Global Ecommerce [3]. Since e-retailers have no physical retail stores, their only option is to store their entire inventory in the warehouses [8, 14]. Consequently, the demand for warehouse space is growing as the economy strengthens and e-commerce surges. National space vacancy rate at US has reached an all-time historic low of 8%, whereas total US expenditures on public and private warehousing rose by 1.8% last year, and forecasters predict steady industry growth of 3% annually through 2021 [6]. Therefore, with the increase in storage costs, warehouse operators are under immense pressure to fulfil increasing customer demands as omni-channel ordering explodes [5].

1.1.2. Third-party service providers. Outsourcing one or more logistical functions to Third-Party Logistics (3PLs) has become a widespread practice in the industry worldwide. The driving force behind this drift is the increasing focus of the companies on their core competencies, from which they can differentiate their product to survive in this highly competitive market [15].

According to Hesse and Rodrigue, third party logistics providers originated from the sole need of warehousing storage back in 1970's [16]. Later during the 1980's, 3PL expanded its services due to the growing need to improve customer satisfaction. Through strategic planning and innovation, 3PLs offered consolidated warehouse and transportation services to reduce the overall operational costs [15]. Today, the business of 3PLs is so much more than just managing warehouses or picking and delivering customers' orders. Nowadays, 3PLs can perform multiple tasks ranging from purchasing raw materials to managing call centers, and are capable of various integrated complex activities in the logistics industry [15].

More and more companies adopt complex supply-chain management strategies and use logistics expertise to obtain a competitive advantage in cost and time efficiency, thereby improving the overall customer satisfaction [17]. The companies now have the ability to focus on their core activities and processes, and outsource the required logistics activities to avoid extensive capital expenditures and to reduce or mitigate risk and uncertainties in their business processes [14]. The expansion of 3PL in the supply-chain through supplementary services is also the result of customization of product or service offerings to customers. Therefore, 3PLs play an important role in the entire logistics process, especially in providing warehousing and transportation services to improve their business processes such as lead-time and fill rate, to match the increasing expectations of the customer [10].

Numerous companies in the supply-chain require the operation of multiple warehouses, ranging from manufacturers and wholesalers to distributors and retailers. As mentioned earlier, considering multiple warehouses has its own set of limitations, therefore, companies usually lease located 3PLs to operate and expand their distribution capabilities. However, the network built can still be considered static, which is to satisfy consistent expected inventory volumes for a long period [8]. However, even the most optimized warehouse network can exceed its limitations in situations that produce temporary or unexpectedly high volume, or a growth profile that differs from the original forecast [14].

Since these traditional models are static, they are either able to handle peak volume and are often underutilized, or are built for average volume and run out of space at peak demand [2]. Beyond these challenges lies the simple issue of scale. Although scale and flexibility are critical, investing billions on distribution centers is largely impossible [14]. Considering all of these challenges, warehouse operators will have to navigate these trends while building holistic, flexible networks capable to providing the rapid order fulfilment today's customer have come to expect [11].

1.2. Technology Driving Towards Collaboration

The Internet and information communication technologies (ICT) are becoming an integral part to the operations of many of today's trucking companies, especially small- to medium-sized firms. Since the advent of the Internet in the 1990s, the freight transportation industry has become more competitive than ever before. To survive in such environment, these carriers have developed new business and operational paradigms [5].

One manifestation of this shift is in the increase in partnership and cooperation among companies, which seeks to exploit synergies in operations. In fact, many small carriers turn to cooperative alliances with the aim of addressing many emerging concerns such as: (i) the increase in requirements by shippers, and (ii) the influence of both the Internet and ICT technologies in increased competition and in the formation of new transportation marketplaces [4]. Thus, the challenge for the carrier collaborative networks will come from being able to address these issues within a cooperative alliance and to create win-win situations for all members in the alliance.

Due to innovative inventory practices and the increased use of e-commerce, shippers, usually larger manufactures and retailers, are increasing their transportation requirements [18]. Increased transportation requirements derive from the fact that demand is becoming more spatially spread, which puts a considerable amount of pressure on the smaller-to medium-sized less-than truckload (LTL) transportation firms to compete and still make a profit. In order to stay competitive, the carrier collaborative must adapt by investing in the latest communication technologies coupled with specialized routing and scheduling, vehicle monitoring, and tracking software. An increased investment in new technologies will provide the collaborative with the ability to reduce some of the inefficiencies in their current operations such as capacity utilization issues (empty trips) and increased competition from other alliances. One manifestation of a web-based solution comes in the form of online transportation market places. Such markets can provide opportunities to strengthen carrier-carrier collaborative, but this method requires the use of the Internet [11].

The Internet, along with information communication technologies (ICT), is pioneering changes to the structure of transportation marketplaces by fostering more spatially spread demand. New transportation marketplaces are emerging from advances in technologies that are used in conjunction with the Internet to match shippers and transportation capacity from virtually anywhere. These transportation exchanges are Internet services that bring together buyers and sellers of inventory and transportation services in order to increase the efficiency of both shipper and carrier operations [18]. These new businesses create opportunities for small- to medium- sized shippers and carriers by providing shipments that allow for an increased utilization of capacity. With the extra demand availability and the worldwide influence of the Internet, competition still becomes an issue. Hence, these new forms of transportation markets in the form of online auctions have fostered competition between the few larger trucking companies and the many small-to-medium ones [1].

Therefore, a collaborative approach would have the ability to close the gap between it and the larger more established competitors by potentially providing sufficient capacity to future shippers, allowing them to compete for the same shipment consignments. Technology advancements and the increased use of Internet-type solutions create opportunities to increase efficiencies through collaborative efforts. Thus, investment in newer and more advanced technologies will provide the necessary tools for seamless connection amongst partners in the collaborative network, allowing them to position themselves more profitably in an already competitive market.

1.3. Technology Essential For Collaboration

The business world is currently experiencing a revolutionary transformation propelled by technological advances such as the seamless Internet availability, telecommunications, navigation and data exchange, making collaboration a opportunity within the logistics industry.

Internet: The increased use of the Internet has nurtured new business paradigms through e- commerce. E-commerce are viewed as the business processes that permit transactions and trade to take place on the web, as well as processes that use the Internet as a repository, an enabler, and a conduit of information [19]. Third party inventory storage and trucking firms are using the Internet to form collaborative alliances through e-commerce opportunities. Internet of things have opened up new possibilities to exploit synergies among collaborators such as determining the capacity availability in real time, to explore newer opportunities for businesses, and to exploit the interconnectedness between collaborators, allowing them to expand their competitive reach to newer markets and improve efficiency to current services areas [20].

Telecommunication: Advances in telecommunications facilitate collaborative efforts by providing the necessary tools for real-time operational information to customers and/or partners [21]. From the perspective of collaboration, telecommunication technologies permit the connectivity of transportation networks through the seamless sharing of collaborative information, such as pickup and delivery of shipments, shipment transfers, and/or on any capacity that may need to be acquired to handle present or future shipments.

Data Exchange and Fusion: Advances in data exchange and fusion technology permit firms under a collaborative network to share information without hindering or jeopardizing their competitiveness in a market. This is made possible through advances in the design of computer systems that ensure the convenient, flexible, secure, and adaptable blending of information from a wide range of independent informational sources [22]. One other form by which this could occur is through what is called secure multiparty computation (SMC). SMC is a cryptographic protocol among a set of participants, where some of the inputs needed for the interaction have to be hidden from participants other than the initial owner [23]. This technology allows a collaborative network to exchange data and to share information critical to the success of the collaborative effort without hindering the firm or its partners.

For centuries, entire businesses have been built and leveraged on the simple principle of trust between multiple parties. However, with the advent of blockchain technology, this entire factor of trust is about to be disrupted. Blockchain can be defined as a system in which a record of transactions can be maintained across a network in a secure manner. By facilitating the move from a centralized to a decentralized and distributed system, blockchain has the potential to essentially remove the need for trusted third-party mediators to verify and record transactions. The industrial applications for this technology is limitless, however, its evident that blockchain applications may have one of the most profound impacts on the logistics industry, especially the supply chain. This is because global supply chains are highly complex with diverse stakeholders, varying interests, and many third-party intermediaries. In the logistics industry, blockchain can be harnessed in two key ways, namely, to drive efficiency and enable new business models:

Drive Efficiency: Blockchain can potentially enhance the efficiency in global trade by greatly reducing bureaucracy and eliminating manual paperwork. Moreover, Blockchain could be used to track a product's lifecycle and ownership transfer from origin to store shelf, even as it changes hands between the manufacturer, logistics service provider, wholesaler, retailer and consumer completely eliminating the need for intermediaries such as insurance, legal, brokerage, and settlement services.

Enable new business models: Just as the Internet began a revolution of communication, blockchain technology could disrupt current business practices and models by introducing micro payments, digital identities, certificates and tamper-proof documents, revolutionizing transparency in the logistics network.

The transformative power of blockchain comes through the unique combination of its differentiating features and characteristics, such as data transparency, security, asset management and smart contracts.

- Data transparency – Blockchain technology includes mechanisms to ensure stored records are accurate, tamper-evident, and from a verifiable source. Thus, instead of multiple parties maintaining (and altering) copies of their own dataset, now every stakeholder receives controlled access to a shared dataset creating a single source of truth. This gives confidence to everyone working with this data that they're using the most recent, accurate, and reliable dataset.

- Security – Traditional ledgers typically provide a blanket layer of security, which, once breached, allows access to all stored data. In a blockchain-based system, the security mechanisms make sure that individual transactions and messages are cryptographically signed. This ensures essential security and effective risk management to tackle today's high risks of hacking and data compromise.
- Asset management – Blockchain technology can be used to manage the ownership of digital assets and facilitate asset transfers. For example, it can be used to track the ownership of titles (e.g., land titles and diamond certificates) and rights (e.g., copyright and mineral rights).
- Smart contracts – Manual processes that are normally guided by legal contracts can be automated with a type of self-executing computer program called a smart contract. A smart contract is a component of a blockchain-based system that can automatically enforce stakeholder-agreed rules and process steps. Once launched, smart contracts are fully autonomous; when contract conditions are met, pre-specified and agreed actions occur automatically.

One of the key aspects in logistics involves working collaboratively with others to optimize the flow of physical goods as well as the complex flow of information and financial transactions, as illustrated in Figure 1. Due to the largely fragmented nature of the logistics industry, many parts of the logistics value chain are bound to manual processes mandated by regulatory authorities, such as the customs processes. This not only increases the cost and processing time, but also reduces the ability to track the provenance of goods, causing loss of transparency in the network. Blockchain has the potential to overcome these frictions, thereby increasing the efficiency in logistics process several folds. This technology can also enable data transparency and access among relevant supply chain stakeholders, creating a single source of truth. In addition, the trust that is required between stakeholders to share information is enhanced by the intrinsic security mechanisms of blockchain technology.

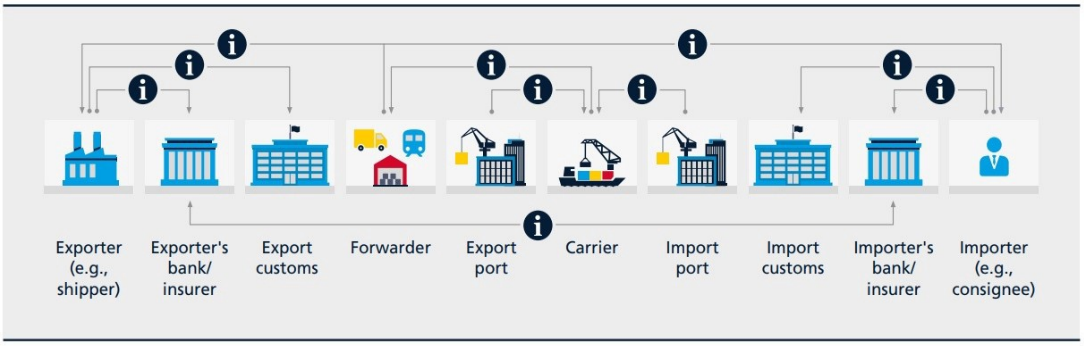


Figure 1: Information flow in a logistics network

Navigation and Positioning: For the collaborative network, near real-time tracking of the fleet is critical in improving efficiency of collaborative capacity over the transportation network [24]. Advances in navigation and positioning technologies have taken trucking from the use of pay phones to relay location information to automatic vehicle location (AVL) systems that constantly track entire fleets in real time [25]. Affordable technology allows firms to collaborate and exploit synergies from both the business and operational standpoints. The success of a collaborative will hinge on the willingness of partners to adapt to the changing times and trends in technology. Depending on the type and level of collaboration, the adoption of specific technologies will often be an essential component to success [21].

1.4. Electronic Logistics Marketplaces: An Emerging Trend

The growing need for transparent, flexible, and easily adjustable logistics services has fostered the creation of digital brokerage platforms that match a variety of logistics demands with supply, widely known as an Electronic Logistics Marketplace (ELM). ELM refers to an electronic hub using web-based systems that link shippers, carriers and customers together for the purpose of collaboration/ trading and facilitate flow of information between the three parties involved by information and communication technology (ICT).

1.4.1. Warehouse marketplace. On-demand warehousing empowers an organization to expand a warehouse network without the burden of capital expenditures, which makes competing with the giants such as Amazon more feasible. Adding flexibility in warehouse capacity increases the ability to respond to demand variability. The flexibility of dynamic warehousing takes the friction out of warehouse expansion, whether for temporary seasonal peaks or product promotions, or on a more permanent basis. Scale becomes instantly available as one taps into unused space across hundreds of warehouses making short-term capacity requirements easier to manage.

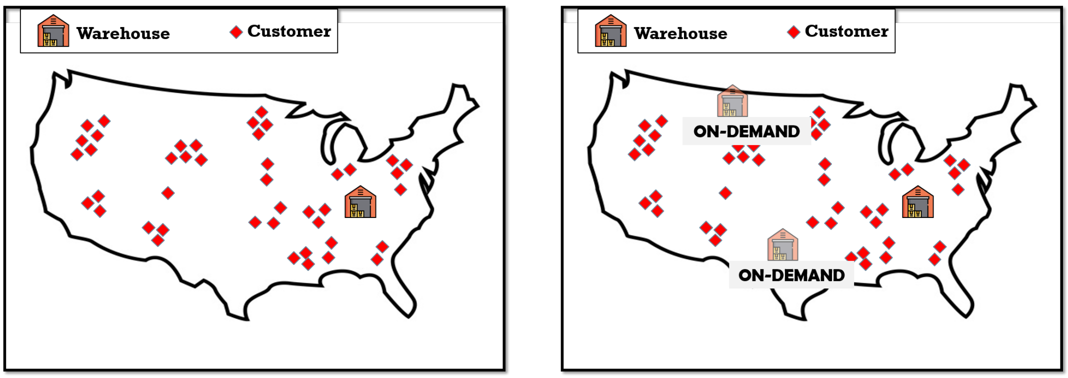
1.4.2. Freight marketplaces. Freight marketplaces match companies looking to ship freight using one or more modes of transport (road, air, ocean, and/or rail) with suppliers or brokers of logistics capacity. The concept of collaboration has been widely accepted in the past 20 years among the various freight companies involved in the full truckload industry and more recently in the less-than-truckload (LTL) industry. Truckload shipper collaboration involves multiple shippers coordinating with one or more carriers and matching their loads so that optimal routing can be found at a minimum cost. In truckload carrier collaboration, multiple carriers reduce operating costs by pooling delivery tasks and vehicle capacities to find efficient ways to fulfill all shipping requests. LTL transportation involves shipping smaller freight, typically from many shippers, and has shorter planning periods than truckload transportation. LTL carrier collaboration can reduce costs by exchanging freight and utilizing one another's capacities. Customers profit from better comparability and transparency of proposals, optimized price/performance ratios, and high security through member certification and rating systems.

1.4.3. Last-mile delivery marketplaces. Last-mile delivery is gaining attention, because of the growth of e-commerce, the increasing customer expectations, and its low efficiency, which leads to challenges for the delivery companies to optimize operation processes and look for innovative solutions. Last-mile delivery marketplace is regarded as one of the solutions for last-mile delivery issues, not only for the logistics providers through better capacity utilization and lower costs, but also for the consumers through flexible delivery schedules and better prices. Consumers can compare quotes, book upfront, and receive auction-style bids from on-demand delivery agents. In many of these peer-to-peer delivery marketplaces, a flexible workforce of private individuals acts as the delivery agent. Such platforms require a critical mass of individuals to participate as agents as well as sufficient platform volume to ensure a sustainable business model.

1.5. Level of Collaboration

The basic principle underlying collaboration is quite simple. By collaborating with potential competitors, companies are integrating multiple supplier and carrier networks allowing the firms to benefit from expanded opportunities [12]. Collaboration itself is enabled by sharing information and enhanced communication between all "collaborating partners." However, two aspects have to be considered depending on the degree of collaboration. The first is the amount of information sharing between the firms, and the second is the communication hub through which the information sharing is facilitated [17].

Since the growth of startups can be highly unpredictable, it is practically impossible to accurately estimate the demands within this cycle. Moreover, the demands of product line can highly differ from one region to the other, and different products might be highly in demand as they increase their product line. These factors by themselves gives rise to huge amounts of uncertainty, making it not viable to increase their distribution network by fixed cost investments [13]. For example, the company has one distribution point from which they may be able to ship 30% of orders within a two-day shipping window, as illustrated in Figure 2a.



(a) Single distribution point (b) On-demand warehousing

Figure 2: On-demand warehousing

Naturally, the company would want to speed up the delivery rate to stay competitive in the market as a response to the increasing demands of customer service. Figure 2b illustrates an on-demand warehousing solution by B2B inventory collaboration to acquire space in strategic locations; hence minimizing overall logistics cost, and effectively increasing the delivery rate to keep up with the increasing customer expectations [1]. From a supply point of view, warehouses would want to enter the platform because they have excess capacity and labor, and are usually even providing these services for themselves. Additionally, on-demand warehousing offers high flexibility on space, hence allowing these e-commerce companies to not be confined with long-term contracts of space that may or may not be used in the nearby future [11].

In recent years, greater driver turnover and deadhead miles, revised hours of operation and heightened security have all contributed to the soaring cost of transportation. Therefore, in this research, inventory and transportation collaboration of firms is mathematically modeled to determine the effect on the overall network efficiency, the costs and their effect on several factors such as customer geographical dispersion and varying demand.

1.6. Research Objectives and Contributions

The main contribution of this thesis is to develop a cooperative approach among the multiple owners of depots for Multi-Depot Vehicle Routing Problem (MDVRP), and determine the effect on the total inventory and transportation cost of the system proposed. Therefore, this thesis proposes a unique shipper-carrier collaboration approach by integrating inventory, long-haul freight transportation and last mile delivery to determine the overall logistics cost of this proposed network. Therefore, the main contributions of this research can be summarized as follows:

- Explore and summarize the existing literature for collaborative models to optimize the logistics of the network.
- Develop a theoretical collaboration mechanism integrating various factors required for valid propositions among partners, which will provide a solid basis for establishing the collaborative network model.

- Develop a business-business collaboration alternative to overcome the most common inventory problems such as peak demand seasonality and underutilization of existing inventory space.
- Determine the responsiveness of the collaborative network model proposed, and compare with the traditional supply-chain model.
- Integrate various components of the supply-chain to observe the overall benefits of the proposed collaborative model in terms of operating flexibility and cost sensitivity to changes in demand.
- Propose an effective heuristic solution to solve a large size realistic problem of the models proposed.
- Identify the possible gaps and limitations in the models proposed, and provide recommendations for future research.

Chapter 2. Literature Review

This chapter presents the related theoretical knowledge and recent work on the various types of collaboration schemes, pricing mechanisms, and the general network characteristics for collaboration.

2.1. Collaboration schemes

The two most common types of collaboration found in literature are the vertical and horizontal collaboration. Vertical collaboration occurs when two or more organizations at different levels of the supply chain such as the manufacturer, distributor and carrier share their resources and responsibilities to serve to achieve a higher level of efficiency and combined savings in their processes. Since the different stages of supply chain are often physically connected by means of freight transportation, carriers fulfilling the role of transportation is one of the most crucial aspects of supply chain collaboration. On the other hand, horizontal collaboration can be defined as a business agreement between two or more companies at the same level in the supply chain or network in order to achieve a shared interest or objective. While the horizontal collaborative concept is relatively new in logistics operations, various strategies and models are researched upon, although most if not all focus in the carriers fulfilling the transportation function to effectively deploy their resources by increasing productivity and decreasing costs, to ultimately improve their service levels and strengthen their market position.

2.1.1. Vertical collaboration. Vertical collaboration could either be done in the planning stage, or some of the resources could be pooled integrating two stages of the supply chain.

2.1.1.1. Collaboration planning stage. Some papers consider the collaboration in planning of supply chain. Zhang et al. [26] consider a multi-echelon production vertically integrating different levels of the supply chain processes. They develop an integrated production planning model to simultaneously manage the supply, fabrication, assembly, and distribution of materials, components, and final products under both supply price and demand quantity uncertainties, while incorporating product structure information and meeting a desired customer service level. Selim et al. [27] consider a collaborative production-distribution planning. They dealt with three level of the supply chain: the manufacturers, the distributors and the retailers. Here, they maximize the profit of the manufacturer and each distributor, and minimize the total cost of each retailer and use fuzzy goal programming to solve the problem.

Jung and Jeong [28] propose a decentralized production-distribution planning system using collaborative agents: one for the distribution and one for the production. They propose two mathematical models, a model to generate a distribution plan from the distribution agent and a model to generate a production plan for the production agent. In their framework, first the distributor agent generates a distribution plan. The desired production amount resulting from the distribution plan is then transferred to the production agent. Ultimately, a production plan is defined to satisfy the distribution plan. Jung et al. [29] propose the same methodology between a manufacturer and a third party logistic provider.

2.1.1.2. Resource pooling. In the collaborative supply chain, partners may also share some resources. In Pan et al. [30], the flow between two stages of supply chain are pooled. Before pooling, flows from suppliers go directly to distribution center. After pooling, upstream or downstream hubs can be created. They formulate a model for this problem at a strategic level considering greenhouse gas emissions, and two modes of transportation, rail and road. Their goal is to minimize the total gas emissions of the network and solve the problem with CPLEX.

2.1.2. Horizontal collaboration. Horizontal collaboration could be done among shippers, carriers, or between shipper and carrier as well.

2.1.2.1. Shipper collaboration. In the shipper collaboration scheme, partners may share information on shipping requirements geared towards improving the transportation performance of shippers. If one shipper has extra needs, it can negotiate with a second shipper in the collaborative community that has excess contracted capacity, thus creating cost savings for both shippers. The first shipper may receive below market prices for carrier capacity, while the second shipper may avoid defaulting with its contract carrier for reneging on contracted capacity [31]. Another widely proposed saving in a full truckload problem is wherein shippers collaborate their routes to minimize empty backhauling to the carriers. Moreover, shippers need to keep up with the exceeding customer expectations, with shorter lead times and often fulfilling less quantities of product ordered by customers. This introduces the topic of less-than-full truckload transportation problem, in which the partners collaborate to minimize their transportation costs.

Only few optimization models on the shipper collaboration problem has been found in literature. Ergun et al. [31] developed one of the first shipper collaborative models that provided the means for shippers to share capacity. These models aimed to lower the costs incurred by transportation providers. Also, mathematical models have been developed for shipper collaboration for truckload (TL) movements based on a set covering formulation with the objective of finding a minimum set of weighted cycles in a network such that all the lanes are covered [31, 32]. Further, they develop heuristics to develop continuous tours. This research is further continued by Özener and Ergun [33], which include a detailed scheme for savings allocation. Game theory is also been applied to several economic models to distribute the costs and savings among the collaborated shippers. One such paper is the research involving horizontal cooperation in linear production processes of manufacturers with a supplier that controls a limited resource [34]. To this end, cooperative game theory and the possibilities of stable distributions of total profit among manufacturers were conducted as a measure of the likelihood of cooperation. Since the manufacturers do not know how the supplier will allocate the limited resource, two main scenarios arise: scarce and insufficient resource or sufficient resources for the grand coalition. For the state involving insufficient resources, the two extreme expectations were analyzed: the optimistic and the pessimistic. In the optimistic case, no conclusion could be attained regarding the full cooperation of the manufacturers. In the pessimistic case, with one reasonable assumption, the existence of stable distributions of the total profit is guaranteed and as a result the collaboration among manufacturers is a win–win deal. Following this, a less-than-truckload shipper collaboration variant is introduced, which first described the necessary requirements for the collaboration, and then proposed two methods for allocating cost-benefits [35]. Song et al., on the other hand, introduce a heuristic pricing allocation mechanism for shipper collaboration with the aim to lower logistics costs and improved asset utilization of both TL and LTL transportation providers. The authors formulate the shipper collaborative problem as a set packing problem that creates continuous move tours that are put out to bid and assigned to carriers [36].

Another recent paper presented a collaborative vehicle routing problem with rough location (CVRPRL), which considers both the security of sharing detailed customer information and the configuration of shared resource [37]. The rough location of the customer was replaced with the detailed customer location, and a concept of collaborative logistics sharing degree was introduced for the CVRPRL model. The proposed model was solved using an extended ant colony optimization (EACO), and the effectiveness of the algorithm was compared with other meta-heuristic algorithms.

2.1.2.2. Shipper-carrier collaboration. Shipper-carrier collaboration, which can also be referred to as collaborative transportation management (CTM), considers collaboration between shippers and carriers where shippers and carriers share on shipment forecast information. Although this type of collaboration tends to be shipper controlled, some neutral exchanges do exist. Such neutral communities typically strive to benefit both parties; therefore, carriers may achieve higher capacity utilization and shippers fewer short shipments through information sharing [38]. The academic literature is mainly focused on improving the relationships between the shipper and primarily TL carriers [38, 39].

2.1.2.3. Carrier collaboration. Finally, carrier collaboration considers the management of their relationships with shippers; meaning that the shippers would not mind having a carrier different from their usual contracted carrier to ship their goods. To accomplish this, the carriers would have to share capacity and shipment information for their own benefit [38]. Therefore, the ability for a carrier, especially a small- to medium-sized one, to make a profit in a highly competitive market between carriers hinges on its ability to minimize its cost over a collaborative network. Recent trends in the freight transportation domain indicate that more and more carriers categorized as small to medium have begun to collaborate as a means to increase slim profit margins and level of competitiveness [40]. In less-than-truckload transportation, the objective is to optimize the capacity utilization of the freight. Whereas in a full truckload collaboration, carriers can jointly minimize backhaul to optimize overall transportation costs.

Song and Regan introduced the notion of carrier collaboration in the TL industry [18]. Carrier collaboration is assumed to occur in a post-market exchange where shipments on non-profitable lanes, assumed to be static and pre- determined by an optimization routine, are auctioned off to other carriers in the collaborative network. Figliozzi (2006) extends the auction-based collaborative carrier network by introducing a dynamic mechanism which is incentive-compatible [41]. The mechanism is analyzed using a simulation procedure for a truckload pick-up and delivery problem. A reduction in dead-heading trips of up to 50% was observed using existing capacity.

Following was an extended carrier collaboration system called the multi-depot capacitated arc which considered another variant of the lane-covering problem (LCP) [42]. Hernandez et al. then addresses a dynamic carrier collaboration problem for a small sized LTL industry [43]. More importantly, a comparison of the collaboration scheme with the short-term leasing is done under various scenarios to establish the benefits of collaboration. Furthermore, Dai and Chen studied the carrier's collaborative problem in a less than truckload transportation for pickup and delivery [44]. They proposed a two-step solution approach to solve the problem. Firstly, a mixed integer-programming model for the problem is proposed and a Lagrangian relaxation approach is developed to solve this model. Secondly, a set of feasible vehicle tours corresponding to the transportation plan of the carriers in collaborative transportation is constructed from the solution of the model. The performance of the proposed model and solution approach is then evaluated by randomly generated instances.

A considerable amount of research is also being steered on designing the structure of such a network and conducting feasibility of horizontal collaboration through theoretical analysis. One such paper is the comparison among two different competitive power structures with and without horizontal coordination [45]. In this research, a game theoretic analysis was conducted on the situation where two logistics service providers compete in an e-commerce logistics market with respect to the order quantity and service level decision on a particular logistics service product. Under a consumer utility-based demand, the equilibrium order quantity decisions and optimal profits under the centralized setting and decentralized setting were obtained. Furthermore, to empower the horizontal carrier coordination, a revenue sharing contract for the decentralized model was designed as well.

In another research, the role of logistics clusters in facilitating horizontal collaboration is researched upon through a systematic literature review methodology [46]. These studies are reviewed under the theoretical lenses of the transaction cost economics (TCE) and the derived identification of governance mechanisms (i.e. joint value propositions, informal governance, formal governance and information exchange) to achieve successful horizontal collaboration. As a result, the effect of logistics clusters to facilitate and promote the development of such mechanisms were described. Moreover, the practice of horizontal logistics in shipping an air-freight is far more widely researched upon with respect to land transport. However, an interesting case study was found that considered four key phases to establish a successful horizontal collaboration initiative, which are the outset consideration factors, ideal synergies, assisting enablers and output metrics [47]. One of the key results were the need for a neutral third-party company in a horizontal logistics initiative due to the risks involved in all the aspects of such a collaboration.

Another widely researched area in carrier collaboration is regarding the profit allocation. A method for sharing profits is using game theory concepts. Krajewska et al. present combined features of routing and scheduling problems and cooperative game theory [48]. They consider a multi-depot pickup and delivery problem with time windows, and solve it using a neighborhood search heuristic. Finally, after analyzing the profit margins resulting from the collaboration, they use the shapley value in game theory to fairly share these profits. Argawan and Ergun model carrier alliances in the liner shipping and determine side payments that align decisions of individual carriers with the decisions of the coalition [49]. Another method for solving this problem is the auction-based approach [50, 51]. In the case of the collaborative carrier problem, an auction allows a carrier to show its interest about a shipment or a bundle of shipments and this information can be used to determine the allocation of the shipments and the allocation of the profits.

2.2. LTL Transportation Collaborative Network Issues and Characteristics

Current collaborative literature deals with some of the obstacles either involved in trying to address shipments that are not desirable by a contracted or preferred carrier, or cannot be served due to some lack in capacity. The following section introduces other characteristics related to LTL carrier collaboration in more depth that need attention when modeling a carrier collaborative system for the small-to-medium-sized LTL trucking industry. These issues and characteristics relate to: (i) shipment time window, (ii) collaborative transfers, (iii) product type, (iv) equipment quality, (v) in-transit and holding costs, (vi) multiple carriers, (vii) pricing mechanism for fair cost allocation, (viii) stochasticity of demand and capacity availability, and (ix) time scale.

2.2.1. Shipment time windows. From the moment an LTL carrier accepts to serve a shipment, the carrier is under the clock to deliver that cargo to its respective customer or client. In the carrier industry, this period of time that is needed to deliver the cargo is known as a time window. A time window is basically a time period defined by the time a shipment is acquired to the time it needs to be delivered [52]. Time windows are an integral part of a collaborative effort since the coordination of the system depends on location of existing capacity, which itself has an associated time availability window that will allow for the on-time delivery of the shipment. Identifying which collaborative carriers are available is dependent upon the time a shipment is received for delivery and the identification of capacity that is available in the network at the needed time. Not all carriers will have capacity available. Situations will arise in which the collaborative carrier (carrier seeking capacity) will have to wait until some capacity is available. This idle time can produce additional costs that the carrier incurs. The capacity may be in transit to the transfer facility or in wait for the unloading of its current cargo at the transfer facility. In such cases, the carrier's collaborative path will be the path that will allow it to meet its time window constraints even though the carrier will have to wait for some time. The challenge then comes from the decision of when a shipment should leave the origin facility and how early it can reach the destination facility. This decision is crucial since available capacity as mentioned earlier may or may not be available at the next facility.

Hence, time windows are one of the most important factors to consider when modeling an LTL carrier-carrier collaborative network since the network configuration changes over time. That is, collaborative capacity is what is considered to be dynamic, since collaborative capacity that is primarily underutilized will be that capacity that is considered excess (for example, capacity at lots, or capacity that would otherwise be an empty haul trip) by the collaborative carriers.

2.2.2. Transfers. In order for a collaborative effort to be efficient, the transfer of shipments between carriers would need to be coordinated to meet time window constraints. A transfer is the loading and/or unloading of a shipment or part of a shipment to be reassigned to another carrier with excess capacity to handle it. A carrier of interest might seek another carrier's excess capacity if that capacity is being offered at a bargain price allowing the carrier of interest to still make a profit, or it might acquire capacity beforehand in anticipation of future shipment demand increases or as in the case of a possible emergency or setback.

The locations of transfers are dependent upon the temporal and spatial availability of capacity. Further, they are dependent on the cost associated with the handling of the transfer. These costs can either be fixed or variable, and these costs can be on a fixed per unit, per weight, or per volume unit basis. These costs may depend on the transfer point (for example, city) in which they occur, as well as incoming and outgoing trucks, for example, the cost of the crew unloading or loading the trailer and any cost associated with the operation of the actual vehicle. From the perspective of a single carrier of interest, if the cost of transferring to use someone else's capacity within the collaborative effort is profitable along an origin-destination pair, a transfer will occur. Still, transfer costs can be very costly—around 5% of the costs incurred by the carrier of interest [53]. One reason that a carrier might transfer its shipment at a transfer facility (warehouse/depot) could be that it has acquired a return shipment increasing its capacity utilization. In addition, it may have no other choice but to acquire capacity because it cannot fully serve the shipment because of lack of capacity.

In a multiple carrier environment, carriers may behave similarly at transfer facilities that have, in general, been the origins or destinations of their operations. A key aspect of the collaborative problem is where to transfer at a minimum cost to meet the time restriction imposed by the shipment and if a transfer is needed.

2.2.3. Product type. Since not all goods are homogeneous and their transportation requirements differ, the type of product to be shipped adds a level complexity to collaboration. Usually a product is simply something of value that can be bought or sold, such as a manufactured good or raw material. Further, a product can be separated into two categories: perishable and non-perishable goods. Perishable products are goods that decay (spoil) or can damage easily (for example, fruits, meats, medical supplies, etc.). The handling of such goods requires special units that can slow the decay process or limit the amount of damage incurred during the transportation phase. Non-perishable commodities are goods of low value and have limited requirements on transport (for example, coal, can goods, etc).

The challenge for a collaborative effort is to match the product type with the appropriate carrying units to facilitate such good. The temporal and spatial availability of such carrying units becomes complex since not all carriers in the collaborative may carry heterogeneous units to facilitate the different product types. Restrictions that contribute to the complexity of the product types are the size or volume of the shipment. There should be enough capacity to accommodate the movement of the product.

Associated with the size of the shipment is the weight of the product. Weight is regulated by each individual state and must be adhered to; this especially applies to non- perishable goods since they tend to be shipped in larger quantities and may weigh much more than perishable goods.

2.2.4. Equipment quality. The quality of the carrier equipment becomes an important factor when dealing with shippers who have specific shipping requirements. For example, perishable consumables can only be shipped on high-quality and refrigerated trailers. Therefore, if a carrier in the collaborative network needs extra capacity to haul these types of goods, it must ensure that the borrowed capacity meets the customer's requirements. In other words, the specialization of the equipment is tied directly to commodity type.

2.2.5. In-transit and holding costs. An important issue to consider in a collaborative effort is the in-transit and holding (idleness) costs. In-transit inventory is inventory on the trucks (units) that is being moved from the origin to destination. Once the shipment has been picked up from the source, the inventory on the trucks begins to incur costs. Given the nature of the product being shipped, these costs can be substantial for a shipper. Moreover, holding costs, which is defined as the costs associated with the idleness of a loaded collaborative carrier waiting to transfer goods to another carrier, can have a considerable impact on the formation of the collaborative routes. Some examples of delays include possible mechanical breakdowns and congestion on the physical network as well as at the terminals, depots, and/or warehouses. In such cases, the holding costs may come from increased pay to the driver for waiting, delivery delay costs (especially on perishable items), potential revenue lost from idled capacity, and increased transfer site fees for utilized space. Thus, the challenge for a collaborative is being able to minimize the effect of these costs on the formation of collaborative routes.

2.2.6. Multiple carriers. In reality, multiple carriers are making individual decisions in order to improve the efficiency of their operations, thereby exhibiting different behavioral tendencies that can affect how collaborative routes are eventually formed. That is, some carriers may be purely revenue driven (these carriers will charge higher collaborative rates independent of how much volume they serve), volume oriented (these carriers are more concerned with establishing density on shipment routes between terminals), or profit oriented (these carriers will adjust rates given the amount of volume shipped). Hence, the challenge from a modeling standpoint is how to account for the varying carrier behavioral tendencies in a single collaborative framework.

2.2.7. Pricing mechanism. Online procurement auctions are being used in varying degrees to dynamically match shipments and transportation capacity. These auctions can provide a powerful means to allocate resources like capacity [40]. Shippers whose preferred carriers have rejected the shipments due to time window constraints, capacity availability, and/or for monetary reasons (shipment may not be profitable) mostly use online procurement auctions in freight transportation. From a carrier perspective, larger carriers who may have accepted shipments that cannot be delivered or serviced may post the shipments online for auction. Therefore, auctions become a tool for both shippers and carriers to allocate the shipments to others that may have the resources to do it (for example, capacity). The drawback is that there is no guarantee that the shipments will be taken during the auction process.

Within a carrier collaborative network, online procurement may not be the best form of allocating shipments and/or resources such as capacity because in an industry like LTL freight, most time windows are relatively short. It would take valuable time, for example, for the carrier to put up the shipments or even capacity to auction with no guarantee of acceptance. One alternative to online procurement is that of hedging for current and future needs. The price can be determined from a various array of potential factors such as current market values, frequency of partnered business (that is, history of working with the same carrier(s)), and guaranteed constant future shipments. Further, the price a carrier is willing to pay for additional capacity from collaborative carriers may depend on various factors, such as amount needed, destination of shipment, pickup and delivery time windows, location of needed capacity, transfers, and product type, to name a few.

As such, price discounts can be gained if capacity is secured beforehand in anticipation of shipment needs. However, the challenges for an LTL carrier-carrier collaborative comes in how to negotiate fair rates amongst the partners in the collaborative network as to ensure a win-win situation for all involved. From an application viewpoint, third party logistics firms (3PL) can potentially provide a carrier collaborative a platform in which to meet. These intermediaries can then provide the necessary technological support (that is, the means to create transactions) to induce collaboration amongst the LTL carriers.

2.2.8. Stochasticity. The stochasticity of shipments and the variability of capacity add additional complexity to LTL collaboration. The competitive nature of the LTL transportation industry is such that shipments can be hard to come by in some regions. In order to secure capacity to fulfill the demand requirements, a carrier must project its needs and hedge for those needs. If the secured capacity is not used, a carrier's profits are trimmed in order to cover the added or unused capacity costs. The carrier can turn around and put its capacity in the market to recover the loss or potentially make a profit.

In practice, not all events can be accurately predicted or even known. Still, collaboration promises potential benefits when carriers undergo unforeseeable events, such as vehicle breakdowns, assuming that a collaborative carrier is nearby with excess capacity. With the advancements in ICT technologies, a carrier in need is just a text message away.

2.2.9. Time scale dimension. Crainic introduced 3 different planning levels: strategic, tactical, and operation planning [50]. The strategic planning horizon refers to a long-term planning such as terminal location, and physical network planning which typically has units of time in weeks, months, and/or years. The tactical planning horizon refers to medium-term planning such as the design of the service network, which may have unit of time in days, weeks, and/or months. In reference to the design of the LTL carrier-carrier collaborative network, these first two planning horizons can be seen as static planning of the collaborative network. That is, these planning horizons would allow for the design of the collaborative network in terms of identifying transfer facilities, and minimizing fuel consumption. The operational planning horizon is defined as the short term horizon that deals with dynamic (time issue) aspects of trucking operations such as driver restrictions, idle time, and availability of collaborative capacity, to name a few.

The availability of collaborative capacity increases the complexity of carrier collaborative models because collaborative capacity is dynamic. That is, the collaborative capacity may be available at one time interval and not the next. Thus, the dynamic nature of the problem requires special attention especially in a highly dynamic LTL industry. When designing the LTL collaborative network, the operational planning horizon can be seen as dynamic planning. That is, the operational planning horizon would allow for the design of the collaborative network in terms of the dynamic nature of the capacity. Likewise, it would allow for the inclusion of other important factors such as in-transit and holding costs. For a carrier collaborative network to succeed, synergies must be exploited in both the planning and operational aspects of such networks. The issues and characteristics presented illustrate the potential for modeling such collaborative efforts amongst carriers and gives direction to addressing the various complexities of such networks. Some of these issues and characteristics go hand-in-hand and need to be addressed in the same modeling framework. For example, a model that imposes some sort of time window must also consider transfers and associated costs. These relationships increase the complexity of the problem.

A major issue that a carrier collaborative network faces is how to best allocate the price and capacity for the collaborative effort. The type of pricing mechanism used can greatly affect the willingness of the carriers to collaborate, especially if there are multiple carriers present with the need for the same capacity. As presented in the literature, an auction-type mechanism can be a solution, but there still exists the possibility that the shipment will not be served.

Planning horizons affect carrier collaboration operations in many different ways. For example, carriers must plan ahead of time or at least have the ability to create operational plans in advance of a shipment. This usually would require carriers to identify the needed equipment, its quality, how will it be shipped (which modes), potential costs, etc. Therefore, to model a carrier collaborative network, these issues and characteristics should be considered in collaborative models to increase the level of the system realism. The next section discusses the approach used to attain the objectives of this thesis.

2.3. Research Methodology

To achieve the goals of this research, the following steps will be followed:

- Perform a comparative study using different distribution strategies in a logistics marketplace.
- Review and update the literature review in the topics of Inventory and Distribution collaboration, Logistics Marketplace, and the operational impact on proposed distribution strategies.

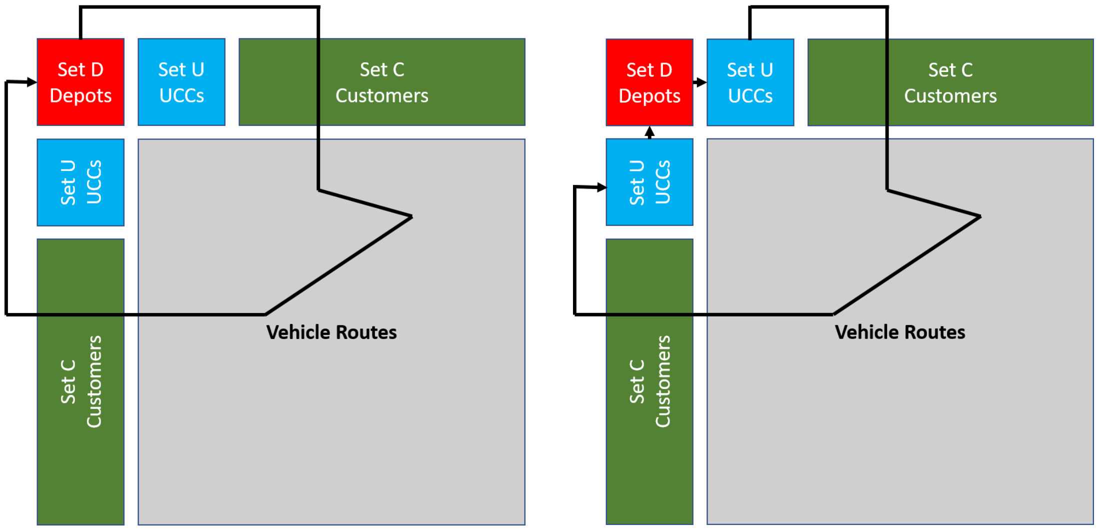
- Formulate and develop the mathematical models representing different levels of inventory and distribution collaboration.
- Solve the developed models using GAMS to find exact solutions and validate the GAMS models using the enumeration approach.
- Examine the behaviour of the models under different levels of geographical customer dispersion and validate the proposition that higher levels of collaboration lead to successively lower distribution costs.
- Select the most cost-efficient model for further exploration.
- Propose an effective heuristic solution to solve a large-sized realistic problem of the selected model.
- Perform sensitivity analysis to determine the most significant aspects of the selected model.

Chapter 3. Comparative Study

The problem encompasses a set of warehouses with supply of specific product types, and a set of customers having weekly product demands, which need to be satisfied. Each of the companies in the network have a single type of product in their warehouse that is to be sold to the customers. The warehouses selected in the network are typically far apart from each other, which are in Sharjah, Dubai and Ras Al Khaimah, if the UAE is to be taken as an exemplary context. The customers are scattered among the three cities, and have weekly product demands. The different product types are of similar characteristics, wherein they are assumed to have identical weights and size. Moreover, each customer can only be served by a single vehicle in the network at any given time. Additionally, the depots and customers in the network are predetermined, and their locations are known beforehand. Furthermore, this thesis encompasses forecasted and real customer demands. For this study, the demand for the various products in the network are forecasted for each city and accumulated for each month, whereas the real customer demands in each city are not known till the beginning of the week, i.e. when the delivery is due. Therefore, the analysis will be conducted for a total of 4 time periods, where each time period has a duration of one week. A typical competitive logistics environment gives rise to various distribution strategies, each having their own merits and demerits. In this research, a comparison approach among three models using different distribution strategies will be used to determine the effect of logistics collaboration on various aspects such as the total logistics cost, responsiveness of the network and sensitivity to demand changes.

The first model, named Model 1 will illustrate the case of no collaboration between the partners. The second model, named Model 2 uses Urban Consolidation Centers (UCC) and finally Model 3 describes the case of inventory and transportation collaboration between the partners in the network. A section will be dedicated to the full description of each model in this chapter, starting with the problem definition, ILP formulations, moving on to the validation of the model and finally its characteristics. We conclude this chapter with a comparison of the characteristics of the three models based on customer geographical dispersion.

The networks in consideration have warehouses as depots, UCC as storage locations for transit, and customers which need to be served exactly once for each time period. Every vehicle needs to be released from their initial positions, i.e. depot or UCC, serve their respective customers and come back to the same position. Therefore, the problem was modeled by constructing a M by M matrix, in which the first nodes is set D, which are the locations of the depots, followed by set U, which are the locations of the UCCs and set C, which are the locations of the customers. This matrix is used in all the models. Figure 3 illustrates how the distance matrix is developed.



(a) Network model with depots and customers

(b) Network model with depots, UCC and customers

Figure 3: Distance matrix for the network models

The following are general simplifying assumptions that we will apply in our analysis for the three models considered:

Model assumptions:

- Each company in the network has only a single depot.
- Each customer can only be served by a single vehicle for each time period.
- The different product types are of similar characteristics, i.e. identical weights and size.
- Each customer can have a demand for only one type of product per time period.
- Each customer can only be served by a single depot per time period.

- The total number of depots and customers in the network are predetermined and their locations are known.
- The real customer demands are known at the start of each week. No customer requests will be carried forward from one period to another, i.e., the demand of every customer in the network should be fulfilled for each period.
- The time period considered for the model is one month, wherein the long-haul transportation (inter-depots supply) is conducted based on expected customer demands at the start of the month, and the last-mile transportation (customer demand) are on a weekly basis based on real customer demands.
- All vehicles must end their route in the same depot in which they started from.
- The vehicles used in the long-haul transportation are different than those of the last-mile transportation.
- The vehicles available in the network will be enough to satisfy the demands of all customers.
- The transportation costs are calculated solely based on the distance covered, disregarding other factors such as the weight of the vehicle.
- The distance travelled for the vehicles are calculated using the Euclidean distance.

3.1. Validation Approach:

To perform the validation of these models, the following approach needs to be conducted:

Step 1: Enumerate manually all the possible routes between the depot or UCC to the customers. Since a solution to the problem constitutes of routes that connect the original depots to the final customers, a solution can possibly contain many routes that correspond to the many vehicles that will be dispatched. This is due to the assumption that all customers need to be satisfied, and there are capacity constraints for each vehicle.

Step 2: Calculate the total cost associated with each feasible solution.

Step 3: Choose the solution that has the minimum overall cost.

For the validation of the models in consideration, an exemplary data set will be constructed. The Validation dataset can be visually described from Figure 4, where the orange icons are the depots, the blue icons are the UCCs, and the green icons are the customers. A simple example of two depots, two UCCs and a total of three customers encompass this network. The existing inventory for each product type at each of the two warehouses is shown in Table 1. By observing Figure 4, it is intuitive that the customers should be satisfied by the depots closest to them. For example, customer C1 and C2 should be satisfied by depot D1 and C3 would be satisfied by depot D2, given that the depots have sufficient inventory. We have intentionally set the customer demands such that each customer demands only the product of the depot closest to it in order to enforce the intuition stated above. Note that in models 1 and 3, UCCs do not exist in the network. The logic of the validation approach is that if the output from the GAMS model matches this intuitive solution and the enumeration approach, then the model is valid.

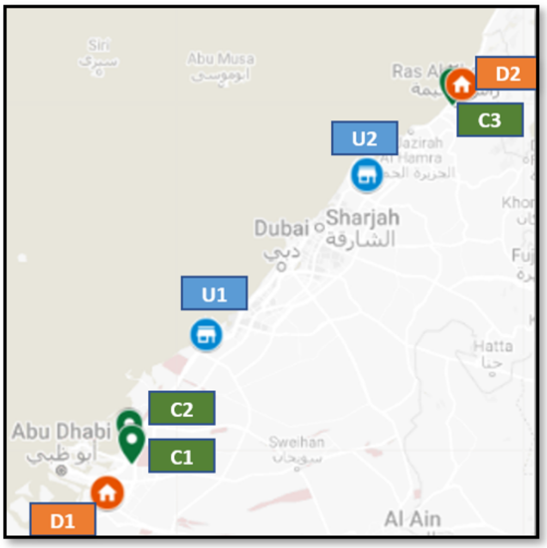


Figure 4: Location of nodes in the validation data set

Table 1: Supply inventory of depots (in units) characterised by product type for the validation data set

	P1	P2
D1	500	0
D2	0	500

In all of the models, we assume that the depots have theoretically infinite large supply of their respective products. We take 500 as a very large number in our implementation. P1 and P2 denote the unique products of depots D1 and D2, respectively, as shown in Table 1.

Manually calculating all possible routes for four time periods will be very time consuming, and hence only one time period will be taken under consideration for validation of the GAMS models. For this reason, the inventory holding cost will not be applicable for the validation approach. Table 2 sets the demands for each product by each customer for the validation dataset. Note that this dataset consists of only three customer nodes and two product types.

Table 2: Demand of each customer (in units) characterised by product type for the validation data set

Time Period	**T1**	
	P1	**P2**
C1	7	-
C2	8	-
C3	-	10

3.2. Characterization approach

We would like to understand how the models behave when customers are geographically dispersed while all other inputs to the models remain constant. Since the objective is to compare the different network models considered, three types of datasets are thoughtfully constructed to understand the model differences under different levels of geographical dispersion.

The primary data required for the development of the different models were the locations of the depot, customer, and UCC nodes, as well as the pairwise distances between each of the nodes. The locations for the depots were chosen as Dubai, Abu Dhabi, and Ras Al-Khaimah based on the assumption that the warehouses in the network should be spatially dispersed. Since the second model employed UCCs for customer fulfillment, each of the two UCC nodes was selected such that they were equidistant from the respective depots.

In the first data set, 9 customer nodes were randomly generated within a 5 km radius from any of the three chosen depots using a random point generator under the assumption that customers are more likely to be clustered around the city. In the second data set, the 9 customer nodes were placed randomly within a 15 km radius from any of the three chosen depots, to understand the effect of varying the depot location with respect to the customers. In the third data set, the same number of customer nodes were now generated within a 25 km radius from any of the three depots in the network. Our objective is to study the effect of customer dispersion with respect to the depots, keeping all the other inputs such as available supply, customer demand and vehicle capacities constant. In order to do this, the distances between each of the aforementioned nodes were obtained from Google Maps, as illustrated in Figure 5. The distance matrix was thereby generated as explained in Figure 3. The existing inventory for each product type at each of the three warehouses is shown in Table 3.

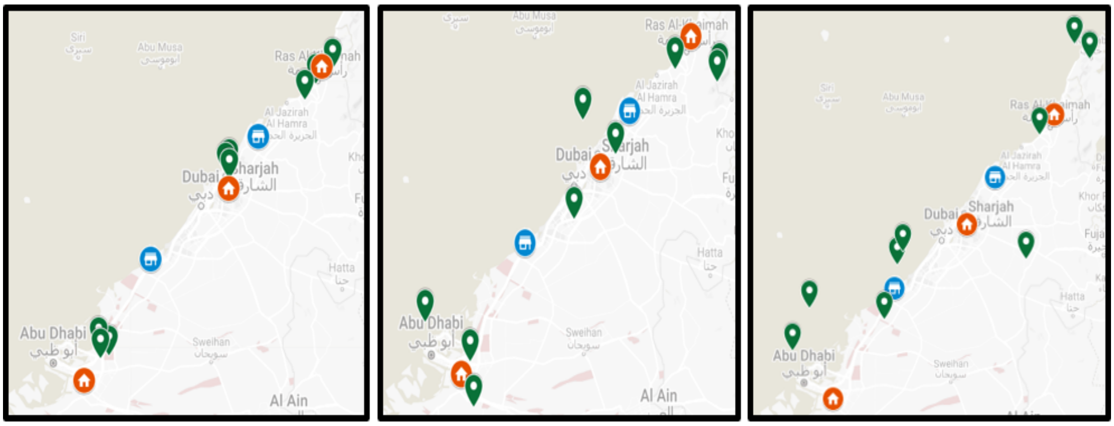


Figure 5: Location of nodes in the characterization data set

We assume that the depots have theoretically infinite large supply of their respective products. We take 500 as a very large number in our implementation. In Table 3, *P1*, *P2*, *P3* denote the unique products of depots *D1*, *D2* and *D3*, respectively.

Table 3: Supply inventory of depots (in units) characterised by product type

	P1	**P2**	**P3**
D1	500	0	0
D2	0	500	0
D3	0	0	500

The various customer demands for each product type for each time period are listed in Table 4. For the purpose of reducing computational time, we assume that each customer will only have demand for a single product type for all the four time periods in consideration.

Table 4: Demand of each customer (in units) characterised by product type

Time Period	**t1**			**t2**			**t3**			**t4**		
	P1	**P2**	**P3**	**P1**	**P2**	**P3**	**P1**	**P2**	**P3**	**P1**	**P2**	**P3**
C1	4	-	-	4	-	-	4	-	-	4	-	-
C2	3	-	-	3	-	-	3	-	-	3	-	-
C3	2	-	-	2	-	-	2	-	-	2	-	-
C4	-	2	-	-	2	-	-	2	-	-	2	-
C5	-	3	-	-	3	-	-	3	-	-	3	-
C6	-	2	-	-	2	-	-	2	-	-	2	-
C7	-	4	-	-	4	-	-	4	-	-	4	-
C8	-	-	2	-	-	2	-	-	2	-	-	2
C9	-	-	1	-	-	1	-	-	1	-	-	1

Before the distribution strategies (demonstrated by Models 1, 2 and 3) are considered, the structure of the model needs to be defined as well. This is important because we are using multiple time periods, for which the outcome of the previous time period affects the results of the future time periods. Table 5 illustrates the idea of the proposed structure to calculate the available supply for all the four time periods considered.

Table 5: Proposed structure to solve the model using sequential approach

	Inputs to the model	**Outputs of the model**
Period 1	• Initial Supply • Real Demand for period 1	• Overall network cost for period 1 • Available supply at the end of period 1
Period 2	• Available supply at the end of period 1 • Real Demand for period 2	• Overall network cost for period 2 • Available supply at the end of period 2
Period 3	• Available supply at the end of period 2 • Real Demand for period 3	• Overall network cost for period 3 • Available supply at the end of period 3
Period 4	• Available supply at the end of period 3 • Real Demand for period 4	• Overall network cost for period 4 • Available supply at the end of period 4

Although, the problem consists of four time periods, the real demands are not known until the start of the period and hence the model cannot be allowed to solve for all the time periods simultaneously. In other words, the model can only be allowed to solve using data that is known by that time period.

For this reason, a proposed solution structure would be to solve the model a total of four times, where the real demand of that time instance was fed to the model. This would be a pure sequential model, in which only the real demands are taken into consideration.

3.3. Types of Cost in Logistics

Total logistics costs consider the whole range of costs associated with logistics, which includes transportation and inventory holding costs, but also order processing, shortage and external costs. Order processing costs is relative to the total volume being handled, and can be simply defined as the expenses incurred to create and process an order to a supplier. However, after the product is manufactured/ packed, the transportation and warehousing costs are the key components when considering the total logistics cost.

The transportation or distribution costs could be split depending on the type of cost incurred. For example, distribution requires regular maintenance of the fleet, and operational costs also include fuel and labor costs. Transport cost can be defined as the sum of the material handling and the shipping costs. Many models are available in literature which shape the transport cost as a function of the transport distance for an assigned class of transport means [4, 50, 51]. For a given transport means and transport distance, the cost of transport can also depend on the speed of the transport means and the shipment size.

Moreover, more detailed costs could be added such as the packaging costs, wrong order costs, utility costs or even the cost of lost/damaged orders while in transit. Even some upfront costs such as planning and development of material handling, and the information systems required for the distribution need to be considered in the overall distribution costs. Additionally, the pricing structure of the less-than truckload transportation greatly varies with the full-truckload transportation scenario, and therefore the distribution strategy greatly affects the overall cost of the network.

However, instead of breaking the overall distribution costs by the type of cost incurred, one can summarize these costs based on the overall cost per order, cost per item or the cost of the customer itself. This can provide a managerial perspective on the cost incurred, which can sometimes provide a better insight than just aggregating all the costs together. Therefore, for the scope of this research, the transportation cost will be considered as a function of transport means adopted and of the transport distance. Since the objective of this research is mainly the comparison of the network models considered, there will be two types of transportation costs for the models considered, namely the line-haul and the last-mile cost, which will be explained in detail later.

Apart from distribution costs, one must also understand the overall warehousing costs. The main expenses are usually the inventory holding cost, for which the rent, labor and utilities are required. There are other costs such as the insurance costs, spoilage/breakage losses, the material handling costs (costs of moving materials and products from one place to another), and even depreciation costs to name a few. Table 6 summarizes the types of warehousing costs and the fee basis for such costs.

Table 6: Breakdown of warehousing costs

Types of warehousing cost	**Fee basis**
Account Setup	Lump Sum
Warehousing storage	Per pallet
Packaging costs	Per pallet
Order fulfilment	Based on volume
Administration and labor costs	Per hour
Returns Management	Per Shipment

The inventory holding cost (warehousing storage cost) mainly depends on the strategy been used. In this model, the net requirements planning in the make-to-stock strategy was selected. Net requirements planning are the requirements for an item based on forecasted customer demand, minus the stock already on hand. In our case, the reorder point is time dependent, in which the required products will be forecasted and bought on a monthly basis. Note that the reorder point for our case is not quantity dependent, and thus the holding costs can simply be calculated as:

$$\text{Holding Cost} = \sum_{t=1}^{4} \text{Remaining inventory}_t * \text{Cost of holding per week}$$

The shortage costs need to be considered in the event that a stock out occurs. However, for the comparative study considered in this thesis, the primary constraint is that all customers have to be satisfied. Therefore, rather than the shortage costs, the network model will incur a higher total distribution cost, since the forecasted demand was not accurate.

External costs are related to the social damages and the environmental impacts, which is mainly addressed in transport activities. Various researches are conducted to estimate the energy consumption and other environmental impacts such as global warming and tropospheric ozone depletion as a result of transportation, in order to attain a more sustainable network model. However, this thesis is focused on leveraging the inventory holding cost through collaboration, in the hopes to create a sustainable network model with lower overall logistic cost. Moreover, the scope of this research is mainly the comparison of the network models considered, and hence only the line-haul and last-mile transportation costs are considered for the distribution costs.

Figure 6 portrays the relationship between total logistics costs and two important cost components; transport and warehousing.

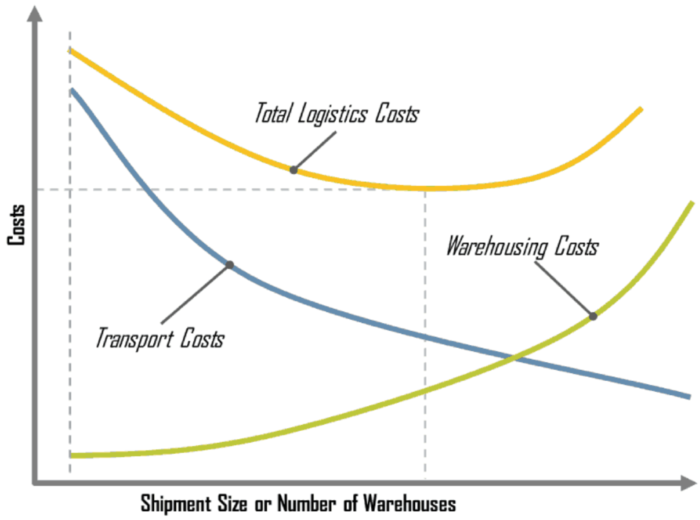


Figure 6: Effect of transportation and warehousing costs on the total logistics cost [54]

Based upon the growth in the shipment size (economies of scale) or the number of warehouses (lower distances), a balancing act takes place between transport costs and warehousing (inventory carrying) costs. There is a cutting point representing the lowest total logistics costs, implying an optimal shipment size or number of warehouses for a specific freight distribution system. Finding such a balance is a common goal in logistical operations and will depend on numerous factors such as if the good is perishable, the required lead time and the market density.

Since the focus of this thesis is conducting a comparative study, we will not consider those types of costs that are equal across all the distribution strategies considered. Furthermore, we will take the total logistics cost as the sum of the inventory cost and the distribution costs, where inventory cost is just the inventory holding cost, while the distribution costs consist of the line-haul and the last-mile costs. The detailed calculations of each type of costs for the models proposed will be explained in sections 3.4.2, 3.5.2 and 3.6.2, respectively.

3.4. Model I: No collaboration between Partners

In this model, each depot is required to serve its own customers since there is no communication or cooperation amongst the companies in the form of sharing warehouse space within the network. Transportation of the deliveries to the end customers are considered to be the last mile transportation, which are scheduled on a weekly basis for a time period of one month. This assumes that the weekly demand of each customer could be of the same product type or of different product types. Moreover, since this is a last-mile transportation, a less-than truckload transportation for these deliveries is considered. The objective is to optimize the cost of network's logistics operations, which mainly includes last-mile transportation costs. Therefore, a classical multi-depot multi-vehicle routing problem is formulated where each company will satisfy its own customers as illustrated in Figure 7.

3.4.1. Problem definition. In this problem, let D represent the number of depot nodes ranging from $D = \{0, 1, 2..., d\text{-}1\}$ and C is the set of customer nodes ranging from $C = \{d, d\text{+}1.., d\text{+}c\text{-}1\}$. For every time period, the vehicles starts its route from its respective depot, satisfies the customers assigned, and comes back to its starting position such that each customer is visited once and only once per time period. Since the depots have supply for only their own unique product, the network will be solved to minimize the total logistics cost such that each depot serves their own customers respectively.

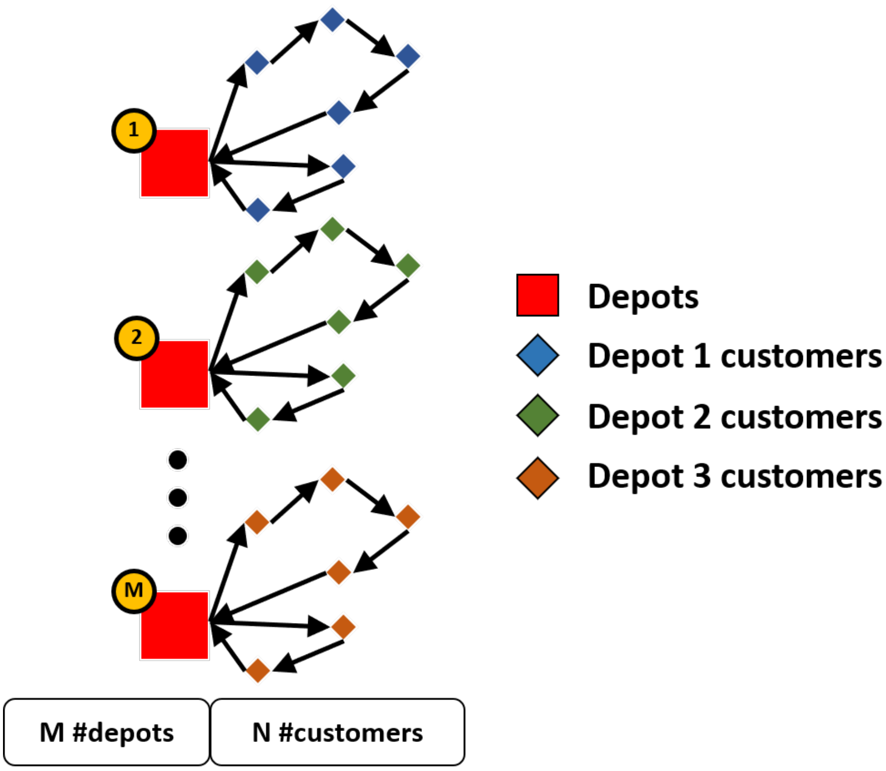


Figure 7: Illustration of the no-collaboration strategy

3.4.2. Network cost assumptions and calculations. In this case, the last-mile cost is the cost of transporting the deliveries from the depots to the customers. We assume that the diesel price is AED 2.41/ liter [55], and the fuel efficiency is 18 liters/ 100 km [56].

Therefore, the price per km for the last-mile delivery is (2.41 x 18)/ 100 = 0.4338 AED/km. The last mile cost per km is denoted by LMC in the mathematical formulation below.

3.4.3. Model formulation.

Sets

D The set of all depots;

C The set of all customers;

U The set of all UCCs.

V The set of all vehicles.

Parameters

N	The total number of customers;
C_{ij}	The distance travelled to go from point i to j, where i,j ∈ D ∪ C;
Sup_{ip}	The supply at depot i for product p;
Dem_{ip}	The demand of customer i for product p;
Cap_k	The capacity of vehicle k.

Decision variables

$$X_{ijkt} = \begin{cases} 1, \text{if vehicle k goes from location i to location j at time t} \\ 0, \text{otherwise} \end{cases}$$

$$Z_{ijt} = \begin{cases} 1, \text{ if customer j is served by depot i at time t} \\ 0, \text{otherwise} \end{cases}$$

U_{ikt} – auxillary variable for subtour elimination of vehicle k at time t

Objective function: Minimize total cost of the network.

$$min \quad \sum_{t\in T} \sum_{i\in D\cup C} \sum_{j\in D\cup C} \sum_{k\in V} LMC * C_{ij} X_{ijkt} \tag{3.1}$$

Subject to the constraints:

- The initial supply is the available supply at time period t1

$$Sup_{ip't1'} = InitS_{ip} \qquad \forall i, p \in D \tag{3.2}$$

- The available supply for each time period is dependent on the previous time period:

$$Sup_{ip(t-1)} - \sum_{j\in C} d_{jpt} Z_{ijt} = Sup_{ipt} \qquad \forall i, p \in D, t \in t2, t3, t4 \tag{3.3}$$

- Each customer node can only be visited once:

$$\sum_{k\in V}\sum_{i\in D\cup C} X_{ijkt} = 1 \qquad \forall j \in C, \forall t \in T \tag{3.4}$$

- The route is limited by the capacity of the vehicle:

$$\sum_{j\in C}\left(\sum_{p\in D} d_{jpt} \sum_{i\in D\cup C} X_{ijkt}\right) \leq Cap_k \qquad \forall k \in V, \forall t \in T \tag{3.5}$$

- Subtour elimination constraint:

$$U_{ikt} - U_{jkt} + NX_{ijkt} \leq N-1 \qquad \forall i \in D\cup C, \forall j \in C, \forall k \in V, \forall t \in T \tag{3.6}$$

- Flow conservation constraint:

$$\sum_{j\in D\cup C} X_{ijkt} - \sum_{j\in D\cup C} X_{jikt} = 0 \qquad \forall i \in D\cup C, \forall k \in V, \forall t \in T \tag{3.7}$$

- Each vehicle can leave their respective depot at most once:

$$\sum_{i\in D}\sum_{j\in C} X_{ijkt} \leq 1 \qquad \forall k \in V, \forall t \in T \tag{3.8}$$

- A customer can only be served by a depot if it has the available capacity for it:

$$\sum_{j\in C} d_{jpt} Z_{ijt} \leq Sup_{ipt} \qquad \forall i, p \in D, \forall t \in T \tag{3.9}$$

- A customer can only be assigned to a depot if there is a route from that depot going through that customer:

$$-Z_{ijt} + \sum_{v\in D\cup C} (X_{ivkt} + X_{vjkt}) \leq 1 \qquad \forall i \in D, \forall j \in C, \forall k \in V, \forall t \in T \tag{3.10}$$

- A customer can be directly served by any of the depots:

$$\sum_{k\in V} X_{ijkt} \leq Z_{ijt} \qquad \forall i \in D, \forall j \in C, \forall t \in T \tag{3.11}$$

- Every customer has to be served by only one of the depots:

$$\sum_{i\in D} Z_{ijt} = 1 \qquad \forall j \in C, \forall t \in T \tag{3.12}$$

3.4.4. Model validation. Since in Model 1 there is no collaboration between any partners and depots only hold their own unique products, therefore the customers' demands have to be satisfied by those depots directly. This means that only last-mile delivery is applicable and therefore there is no line-haul transportation for this model. Moreover, since only one time period is considered, there will be no inventory holding cost. By solving the model manually, we obtained two possible solutions as shown in Table 7.

Table 7: Enumeration of feasible solutions for Model 1

Feasible Solutions	Routes	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Total Cost (AED)
Solution 1	D1-C1-D1 D1-C2-D1 D2-C3-D2	0	35.51	35.51
Solution 2	D1-C1-C2-D1 D2-C3-D2	0	33.87	33.87

In the first solution, there are three routes corresponding to three vehicles which will be dispatched to satisfy the orders of the customers. The notation D1-C1-D1 means that the vehicle shall depart from D1, fulfil C1 and return back to D1. The optimal solution was found to be solution 2, and the GAMS model has provided the same result. It can be noticed that solution 1 uses 3 vehicles, whereas solution 2 merges the first two routes since the vehicle has available capacity, thereby using only two vehicles. It is known that even small size TSP problems can be very difficult to solve, since this is a NP-Hard problem. Since all the vertices in the graph correspond to points in the metric space, such that the weight between any two vertices correspond to the Euclidean distance between the respective points, the triangle inequality holds for this problem. Therefore, it can be proved that merging the two routes together will always lead to a more optimal route using the triangle inequality theorem [57]. Therefore, the triangle inequality theorem can be used to reduce the number of possible optimal solutions to be assessed for the enumeration approach.

3.4.5. Model characteristics. After running the validated GAMS model using the characterization dataset, we obtained the total logistics cost in for each level of customer geographical dispersion, and is reported in the Table 8.

Table 8: Results of Model 1 characterization

Geographical dispersion	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Inventory Holding Cost (AED)	Total Cost (AED)
5KM	0	4458.04	0	4458.04
15KM	0	5052.44	0	5052.44
25KM	0	5200.4	0	5200.4

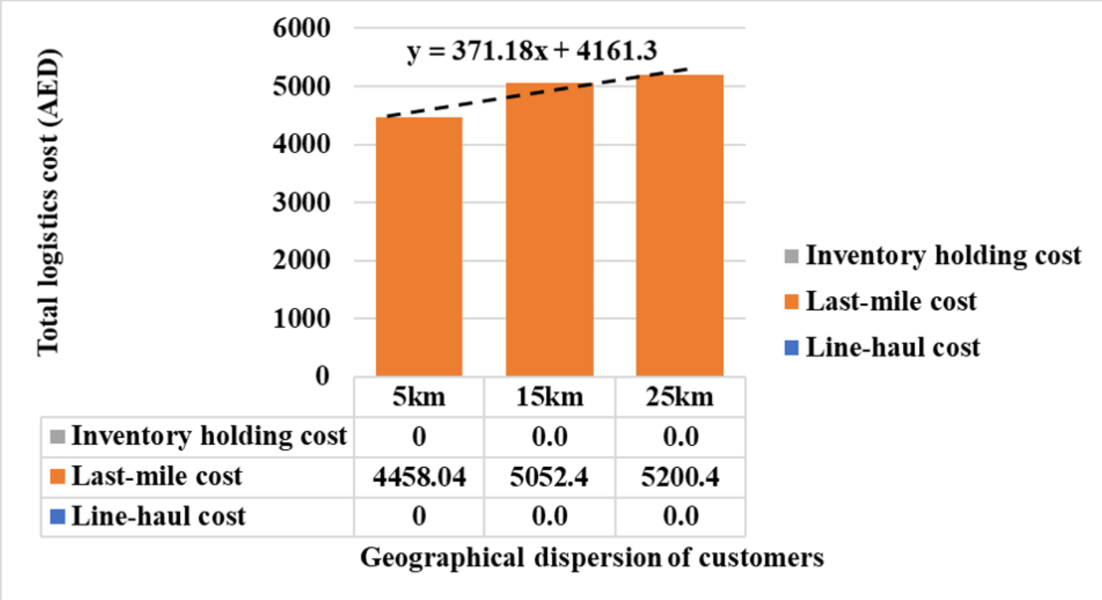


Figure 8: Total logistics cost(y) vs geographical dispersion of customers(x): Model 1

Over the range of 5 km to 25 km geographic dispersion, the total cost seems to follow a linear trendline, whose slope indicates that on average the increase in the total logistics cost is 371 AED for every 1 km increase of customer dispersion relative to the depots. Figure 8 also shows the contribution of the last-mile, line-haul and inventory costs to the total logistics cost for each level of customer dispersion. As mentioned above, only last-mile cost is applicable in Model 1.

3.5. Model 2: Partner collaboration- Urban Consolidation Centers (UCC) Approach

This model involves some level of cooperation and communication among the warehouses wherein all the network partners consolidate their products to third-party Urban Consolidation Centers (UCCs). These UCCs, in turn, fulfil all the customer demands as illustrated in Figure 9. The UCCs allow the companies to store their respective products collectively, thus creating a network which allows the fulfillment of different product type demands of customers.

In this case, the distribution is two-fold. On the one hand, the deliveries to the UCCs are considered to be line-haul, which is why a full-truckload transportation is assumed. These line-haul deliveries are expected to be of rather long-distances, and therefore the inventory is delivered for the entire month considered according to the predetermined expected or forecasted demand. On the other hand, the deliveries to the end customers are considered last mile transportation, and thus, scheduled on a weekly basis for the month in study. Similar to the previous model, this case also considers less-than truckload deliveries for the last mile transportation. However, it is to be noted that resource-sharing amongst the partners does not take place within this model.

3.5.1. Problem definition. In this problem, let D represent the number of depot nodes ranging from $D = \{0, 1, 2..., d\text{-}1\}$ and C is the set of customer nodes ranging from $C = \{d, d+1.., d+c\text{-}1\}$. For every time period, the vehicles starts its route from its respective depot, satisfies the customers assigned, and comes back to its starting position such that each customer is visited once and only once per time period.

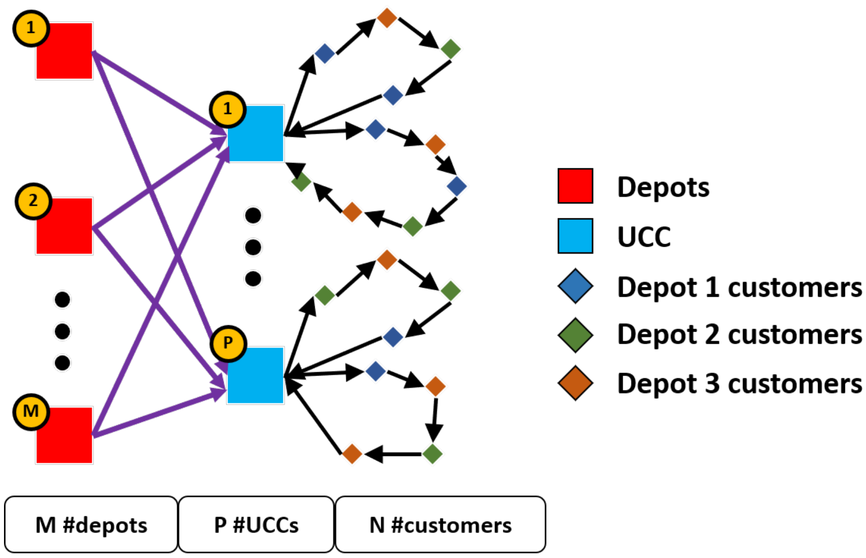


Figure 9: Illustration of the Urban Consolidation Centers (UCC) distribution strategy

3.5.2. Network cost assumptions. In this distribution strategy, the total logistics costs comprise of inventory costs and distribution costs. The line-haul transportation is the shipping of the forecasted demand for the next four periods from the depots to the UCCs, while last-mile transportation is the delivery of products from the UCCs to the customers. Both last-mile cost and line-haul cost per km are calculated as the product of the diesel cost and the fuel efficiency of the vehicles. The diesel cost was assumed to be AED 2.41/L [55]. The fuel efficiency and the price/ km calculations can be found in Table 9. We assume that the vehicles used for the last-mile delivery are smaller and therefore more fuel efficient than those used in line-haul deliveries.

Table 9: Transportation cost breakdown for Model 2

	Fuel efficiency /100km	**Price/km calculation**
Last-mile	12L [56]	(2.41*12)/100 = 0.2892 AED/km
Line-haul	20L [58]	(2.41 x 20)/100 = 0.482 AED/km

The inventory holding cost is simply calculated as the product of the closing inventory in each UCC at the end of each week, the holding cost per unit volume and the volume per unit. The assumed values for the holding cost per unit volume is AED 0.05 [59], and the volume per unit is 19 L.

3.5.3. Model formulation.

Objective function: Minimize total cost of the network.

$$min \sum_{t\in T}\sum_{i\in U\cup C}\sum_{j\in U\cup C}\sum_{k\in V}(LMC*C_{ij}X_{ijkt}) + \sum_{i\in U\cup D}\sum_{j\in U\cup D}(LHC*DepotUcc_{ij}Y_{ij}) + \sum_{t\in T}\sum_{i\in U\cup D}\sum_{j\in U\cup D}\sum_{p\in D}(H*Inv_{ijpt}) \tag{3.13}$$

Subject to the constraints:

- The expected demand has to be fulfilled from the line-haul transportation

$$Sup_{ip't1'} = InitS_{ip} + ED_{ip} * Y_{pi} \qquad \forall i,p \in D \tag{3.14}$$

- Only those units are to be transported between depots which are not available in the initial supply:

$$ED_{ip} - InitS_{ip} \leq 1000 * Y_{pi} \qquad \forall i,p \in D \tag{3.15}$$

- The available supply for each time period is dependent on the previous time period:

$$Sup_{ip(t-1)} - \sum_{j\in C} d_{jpt}Z_{ijt} = Sup_{ipt} \qquad \forall i,p \in D, t \in t2,t3,t4 \tag{3.16}$$

- Each customer node can only be visited once:

$$\sum_{k \in V} \sum_{i \in U \cup C} X_{ijkt} = 1 \qquad \forall j \in C, \forall t \in T \tag{3.17}$$

- The route is limited by the capacity of the vehicle:

$$\sum_{j \in C} (\sum_{p \in U} d_{jpt} \sum_{i \in U \cup C} X_{ijkt}) \leq Cap_k \qquad \forall k \in V, \forall t \in T \tag{3.18}$$

- Subtour elimination constraint:

$$U_{ikt} - U_{jkt} + NX_{ijkt} \leq N - 1 \qquad \forall i \in U \cup C, \forall j \in C, \forall k \in V, \forall t \in T \tag{3.19}$$

- Flow conservation constraint:

$$\sum_{j \in U \cup C} X_{ijkt} - \sum_{j \in U \cup C} X_{jikt} = 0 \qquad \forall i \in U \cup C, \forall k \in V, \forall t \in T \tag{3.20}$$

- Each vehicle can leave their respective UCC at most once:

$$\sum_{i \in U} \sum_{j \in C} X_{ijkt} \leq 1 \qquad \forall k \in V, \forall t \in T \tag{3.21}$$

- A customer can only be served by a UCC if it has the available capacity for it:

$$\sum_{j \in C} d_{jpt} Z_{ijt} \leq Sup_{ipt} \qquad \forall i, p \in U, \forall t \in T \tag{3.22}$$

- A customer can only be assigned to a UCC if there is a route from that depot going through that customer:

$$-Z_{ijt} + \sum_{v \in U \cup C} (X_{ivkt} + X_{vjkt}) \leq 1 \qquad \forall i \in U, \forall j \in C, \forall k \in V, \forall t \in T \tag{3.23}$$

- A customer can be directly served by any of the UCCs:

$$\sum_{k \in V} X_{ijkt} \leq Z_{ijt} \qquad \forall i \in U, \forall j \in C, \forall t \in T \tag{3.24}$$

- Every customer has to be served by only one of the UCCs:

$$\sum_{i \in U} Z_{ijt} = 1 \qquad \forall j \in C, \forall t \in T \tag{3.25}$$

- Inventory can only be transported from a depot to a UCC if a vehicle goes from that depot to that UCC:

$$\sum_{i \in D} Inv_{ijpt} = Sup_{jpt} \qquad \forall j, p \in D, \forall t \in T \tag{3.26}$$

- The depot can only transport to the UCC if it has available supply:

$$Sup_{ijpt} \leq InitS_{ip} Y_{ij} \qquad \forall i, p \in D, j \in U, \forall t \in T \tag{3.27}$$

- The vehicle must come back to its depot, either full truckload or empty:

$$Y_{ij} = Y_{ji} \qquad \forall i \in D, j \in U, \forall t \in T \tag{3.28}$$

- Every customer has to be served by only one of the UCCs:

$$\sum_{j \in U} Sup_{ijpt} \leq InitS_{ip}, \forall t \in T \tag{3.29}$$

3.5.4. Model validation. In Model 2, both UCCs can potentially satisfy all customers in the network, which leads to a large number of possible solutions.

Table 10: Enumeration of feasible solutions for Model 2

Feasible Solutions	Routes	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Total Cost (AED)
Solution 1	U1-C1-C2-U1 U2-C3-U2	75.19	110.62	185.81
Solution 2	U1-C1-C3-U1 U2-C2-U2	212.43	330.71	543.13
Solution 3	U1-C2-C3-U1 U2-C1-U2	212.43	330.73	543.16
Solution 4	U1-C1-C2-C3-U1	128.15	199.02	327.17
Solution 5	U2-C1-C2-C3-U2	128.80	199.27	328.07
Solution 6	U1-C1-U1 U2-C2-C3-U2	159.47	241.85	401.32
Solution 7	U1-C2-U1 U2-C1-C3-U2	159.47	241.76	401.23
Solution 8	U1-C3-U1 U2-C1-C2-U2	181.76	288.45	470.21
Solution 9	U1-C1-C3-C2-U1	128.15	241.26	369.41
Solution 10	U1-C2-C1-C3-U1	128.15	198.96	327.11
Solution 11	U2-C1-C3-C2-U2	128.80	330.43	459.23
Solution 12	U2-C2-C1-C3-U2	128.80	199.22	328.02

In Model 2, customers can only be fulfilled from the UCCs which have no inventory of any product in the first time period in our model. Therefore, line-haul delivery is required from the depots to the UCCs based on forecasted customer demands for each product. For example, U1 is satisfying C1 and C3, where C1 requires P1 from D1, C3 requires P2 from D2. Therefore, there will be a line haul cost from both D1 and D2 to U1. In this example, all the customers are closer to the depots than the UCCs, resulting in high last mile costs. By solving the model manually, we obtained several possible solutions as shown in Table 10. Based on the manual enumeration method, solution 1 is the optimal solution which also agrees with the GAMS model.

3.5.5. Model characteristics. After running the validated GAMS model using the characterization data set, we obtained the total logistics cost in for each level of customer geographical dispersion, and is reported in Table 11.

Over the range of 5 km to 25 km geographic dispersion, the total cost seems to follow a linear trendline, whose slope indicates that on average the increase in the total logistics cost is 247 AED for every 1 km increase of customer dispersion relative to the depots. It is noted that the rate of increase of the total logistics cost of Model 2 is 33.26% less than that of Model 1. Figure 10 shows the contribution of the last-mile, line-haul and inventory costs to the total logistics cost for each level of customer dispersion. As the geographical dispersion of customers increases, the contributions of inventory costs and line-haul costs decrease while that of last mile cost increases.

Table 11: Results of Model 2 characterization

Geographical dispersion	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Inventory Holding Cost (AED)	Total Cost (AED)
5KM	245.46	951.11	249.86	1446.43
15KM	245.46	1265.31	249.86	1760.63
25KM	245.46	1446.59	249.86	1941.91

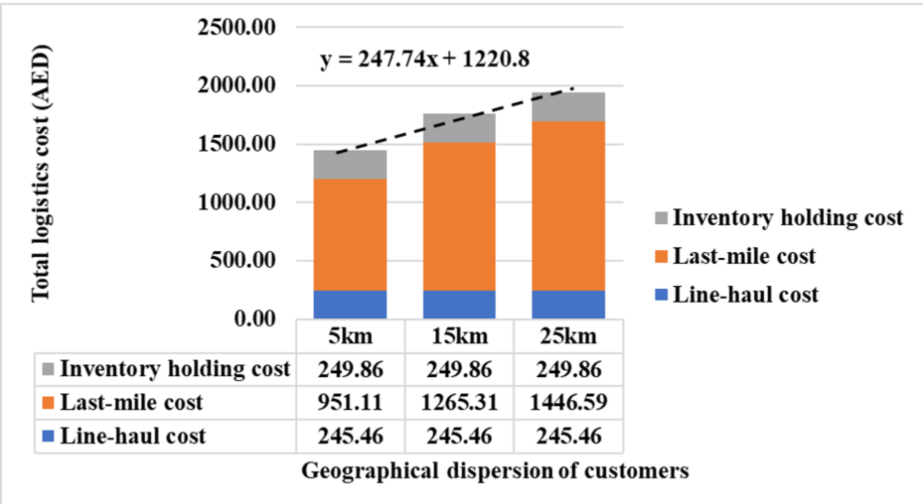


Figure 10: Total logistics cost(y) vs geographical dispersion of customers(x): Model 2

3.6. Model 3: Inventory and Distribution Collaboration between Partners

In this model, there is high level of collaboration among the companies. It comprises of both inventory and freight collaboration, by which any of these warehouses will have the capability of fulfilling their partner's customer needs based on the available supply and anticipated demands as illustrated in Figure 11.

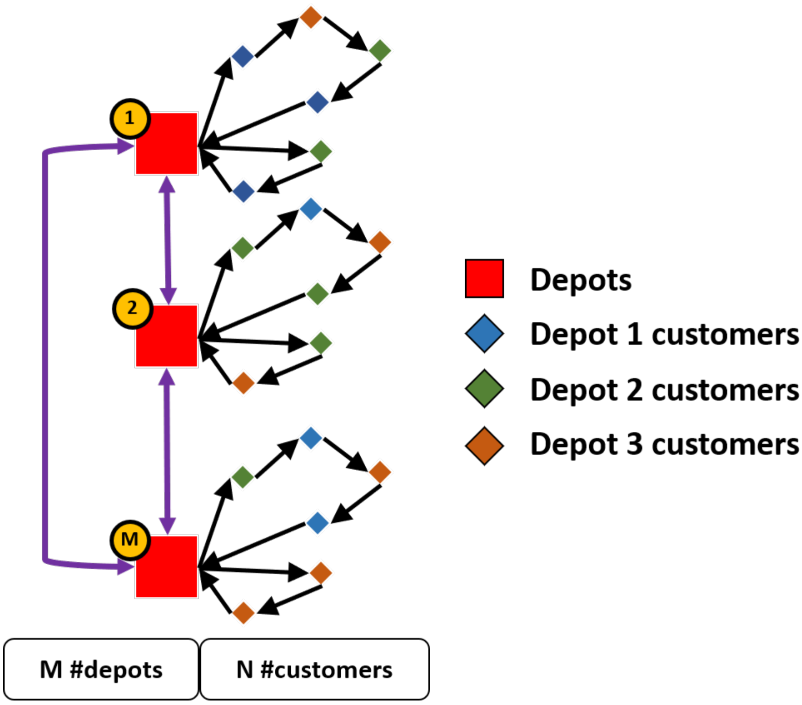


Figure 11: Illustration of inventory collaboration as a distribution strategy

Inventory collaboration among the warehouses makes it possible to share their existing inventory storage spaces so as to minimize transportation costs, allowing one warehouse to store the products of other warehouses to satisfy the customers which are closest to them.

Similar to the previous model, the distribution is two-fold. On the one-hand, deliveries within the depots are considered to be line-haul, due to which the inventory is delivered for the entire one-month considered. A full-truckload scenario is considered for the line-haul transportation. On the other hand, the deliveries to the end customers are considered to be last mile transportation, and thus, scheduled on a weekly basis for the month in study. All the models considered less-than truckload deliveries for the last mile transportation. This model closely represents the on-demand warehousing approach to counter many of the challenges in a supply-chain network as described earlier in this thesis.

3.6.1. Problem definition. In this problem, let D represent the number of depot nodes ranging from $D = \{0, 1, 2..., d\text{-}1\}$ and C is the set of customer nodes ranging from $C = \{d, d+1.., d+c\text{-}1\}$. For every time period, the vehicles starts its route from its respective depot, satisfies the customers assigned, and comes back to its starting position such that each customer is visited once and only once per time period.

3.6.2. Network cost assumptions. In this distribution strategy, the distribution costs and the inventory costs encompass the total logistics cost of the network. Similar to the previous distribution strategy, the last-mile and line-haul cost per km are calculated as the product of the diesel cost and the fuel efficiency of the vehicles. The diesel price is assumed to be AED 2.41/L [55]. The fuel efficiency and the price/km calculations can be found in Table 12.

Table 12: Transportation cost breakdown for Model 3

	Fuel efficiency /100km	**Price/km calculation**
Last-mile	18L [56]	(2.41*18)/100 = 0.4338 AED/km
Line-haul	20L [58]	(2.41 x 20)/100 = 0.482 AED/km

We assume that identical line-haul trucks were used in this distribution strategy as compared to the ones used in the UCC collaboration scenario. It is to be noted that the vehicles used in the last-mile transportation are less fuel efficient (consume more fuel per km) than that of the UCC collaboration scenario, under the assumption that the 3PL have a more efficient distribution system.

The inventory holding cost is calculated as the product of closing inventory in each depot at the end of each week, the holding cost per unit volume and the volume per unit. The inventory cost for products in their original depots is taken as zero because we have assumed that there is an infinite supply of a product at its original depot (therefore an infinitely high inventory cost is not realistic). Moreover, the assumed values for the holding cost per unit volume is AED 0.05 [59], and the volume per unit is 19L. The next section entails the model formulation of the described network.

3.6.3. Model formulation.

Objective function: Minimize the overall logistics cost of the network.

$$\begin{aligned} min \quad & \sum_{t\in T}\sum_{i\in D\cup C}\sum_{j\in D\cup C}\sum_{k\in V}(LMC * C_{ij}X_{ijkt}) \\ & + \sum_{i\in D}\sum_{j\in D}(LHC * DepotDepot_{ij}Y_{ij}) \quad + \sum_{t\in T}\sum_{i\in D}\sum_{j\in D}\sum_{p\in D}(H * Inv_{ijpt}) \end{aligned} \tag{3.30}$$

Subject to the constraints:

- Each customer node can only be visited once:

$$\sum_{k\in V}\sum_{i\in D\cup C} X_{ijkt} = 1 \qquad \forall j\in C, \forall t\in T \tag{3.31}$$

- The route is limited by the capacity of the vehicle:

$$\sum_{j\in C}(\sum_{p\in D} d_{jpt}\sum_{i\in D\cup C} X_{ijkt}) \leq Cap_k \qquad \forall k\in V, \forall t\in T \tag{3.32}$$

- Subtour elimination constraint:

$$U_{ikt} - U_{jkt} + NX_{ijkt} \leq N-1 \qquad \forall i\in D\cup C, \forall j\in C, \forall k\in V, \forall t\in T \tag{3.33}$$

- Flow conservation constraint for the last mile delivery:

$$\sum_{j\in D\cup C} X_{ijkt} - \sum_{j\in D\cup C} X_{jikt} = 0 \qquad \forall i\in D\cup C, \forall k\in V, \forall t\in T \tag{3.34}$$

- Each vehicle can leave their respective depot at most once:

$$\sum_{i\in D}\sum_{j\in C} X_{ijkt} \leq 1 \qquad \forall k\in V, \forall t\in T \tag{3.35}$$

- The available supply for each time period is dependent on the previous time period:

$$Sup_{ip(t-1)} - \sum_{j\in C} d_{jpt}Z_{ijt} = Sup_{ipt} \qquad \forall i,p\in D, t\in t2,t3,t4 \tag{3.36}$$

- A customer can only be assigned to a depot if there is a route from that depot going through that customer:

$$-Z_{ijt} + \sum_{v\in D\cup C}(X_{ivkt} + X_{vjkt}) \leq 1 \qquad \forall i\in D, \forall j\in C, \forall k\in V, \forall t\in T \tag{3.37}$$

- A customer can be directly served by any of the depots:

$$\sum_{k\in V} X_{ijkt} \leq Z_{ijt} \qquad \forall i\in D, \forall j\in C, \forall t\in T \tag{3.38}$$

- Every customer has to be served by only one of the depots:

$$\sum_{i\in D} Z_{ijt} = 1 \qquad \forall j \in C, \forall t \in T \tag{3.39}$$

- The expected demand has to be fulfilled from the line-haul transportation

$$Sup_{ip't1'} = InitS_{ip} + ED_{ip} * Y_{pi} \qquad \forall i, p \in D \tag{3.40}$$

- Only those units are to be transported between depots which are not available in the initial supply:

$$ED_{ip} - InitS_{ip} \leq 1000 * Y_{pi} \qquad \forall i, p \in D \tag{3.41}$$

- The flow conservation constraint for the line-haul transportation:

$$\sum_{p\in D} Y_{ip} - \sum_{p\in D} Y_{pi} = 0 \qquad \forall i \in D \tag{3.42}$$

- There can not be line-haul transportation of units within the same depot

$$Y_{ii} = 0 \qquad \forall i \in D \tag{3.43}$$

3.6.4. Model validation. In contrast to Model 2, no UCCs exist in this model and depots can now collaborate directly, therefore line-haul costs will result from inter-depot line-haul transportation. All depots can potentially satisfy all customers, given they have the required inventory. Table 13 enumerates all of the possible solutions for this model. It is observed that the optimal solution obtained was the same as that of the no collaboration scenario. This is because the customers were very close to the depots (recalling that each customer demanded only the product of its nearest depot), therefore no inter-depot line-haul was required. However, the solution is highly dependent on the dataset used, and the difference between the two models can be seen more effectively in the next section.

3.6.5. Model characteristics. After running the validated GAMS model using the characterization dataset, we obtained the total logistics cost in for each level of customer geographical dispersion, and is reported Table 14. Over the range of 5 km to 25 km geographic dispersion, the total cost seems to follow a linear trendline, whose slope indicates that on average the increase in the total logistics cost is 314 AED for every 1 km increase of customer dispersion relative to the depots. It is noted that the rate of increase of the total logistics cost of Model 3 is 15.4% less than that of Model 1, however it is 27% higher than that of Model 2. However, it can be seen that Model 3 results in a much lower overall logistics cost as compared to Model 1 and Model 2.

Table 13: Enumeration of feasible solutions for Model 3

Feasible Solutions	Routes	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Total Cost (AED)
Solution 1	D1-C1-C2-D1	0	33.87	33.87
	D2-C3-D2			
Solution 2	D2-C1-C2-C3-D2	192.01	217.57	409.57
Solution 3	D1-C1-C2-C3-D1	192.01	200.09	392.09
Solution 4	D1-C2-D1	192.01	227.07	419.08
	D2-C1-C3-D2			
Solution 5	D1-C1-D1	192.09	217.80	409.81
	D2-C2-C3-D2			
Solution 6	D2-C2-C1-C3-D2	192.09	217.59	409.60
Solution 7	D2-C1-C3-C2-D2	192.09	402.92	594.93
Solution 8	D1-C2-C1-C3-D1	192.09	207.75	399.96
Solution 9	D1-C1-C3-C2-D1	192.09	200.34	392.35

We can see that Solution 1 is the optimal solution which also agrees with the output from the GAMS model.

Table 14: Results of Model 3 characterization

Geographical dispersion	Line-Haul Cost (AED)	Last-Mile Cost (AED)	Inventory Holding Cost (AED)	Total Cost (AED)
5KM	426.69	227.59	185.72	840
15KM	426.69	542.18	185.72	1154.59
25KM	426.69	855.56	185.72	1467.96

The characterization of Model 3 can also be found in Figure 12. It also illustrates the contribution of the last-mile, line-haul and inventory costs to the total logistics cost for each level of customer dispersion. From Table 14, we observe that in all three cases, the inventory costs and line-haul costs are constant while last-mile costs increase. This means that as the geographical dispersion of customers increases, the contributions of inventory costs and line-haul costs decrease while that of last mile cost increases. While Model 2 characteristics follow the same general trend, i.e. increasing proportion of last-mile cost with increase in customer dispersion, it is accentuated and more visible in Model 3. The line-haul and inventory holding cost have no effect on customer dispersion as expected.

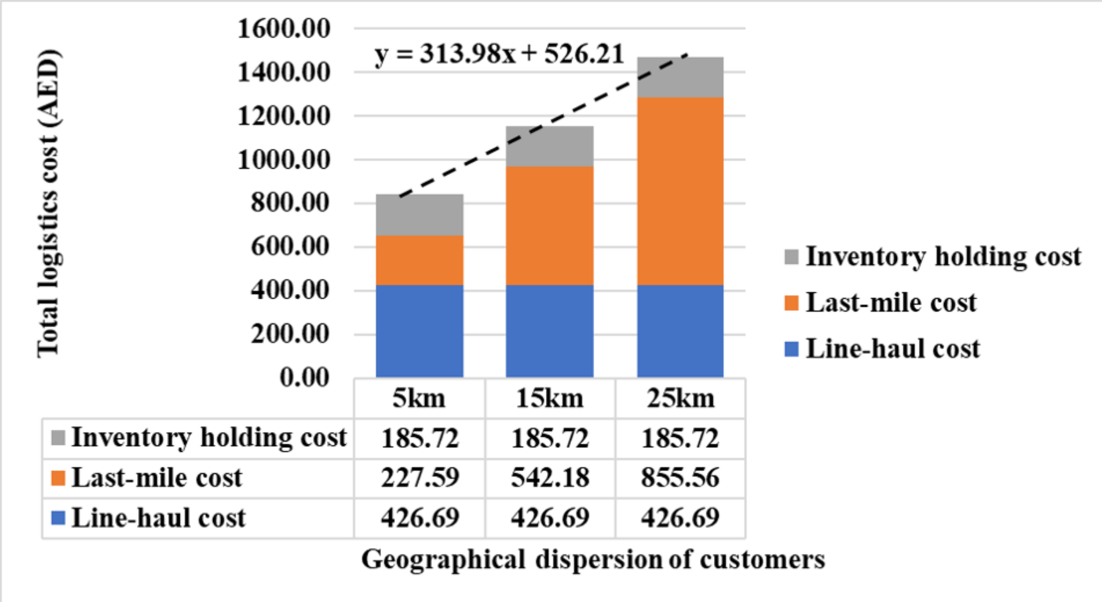


Figure 12: Total logistics cost(y) vs geographical dispersion of customers(x): Model 3

3.7. Comparison of the Models Proposed

In this section, we summarize and compare the outputs of the three models for the three levels of geographical customer dispersion. Table 15 displays the total logistics cost for each model and for each case. The savings were calculated based on the total costs of Model 1, since it always resulted in the highest cost in each case. We also note from the table, that Model 3 consistently resulted in the greatest percentage savings.

Table 15: Total logistics cost for all distribution strategies proposed

	Case 1: 5KM		**Case 2: 15KM**		**Case 3: 25KM**	
	Total Cost (AED)	**Savings**	**Total Cost (AED)**	**Savings**	**Total Cost (AED)**	**Savings**
Model 1	4458.04	-	5052.44	-	5200.4	-
Model 2	1446.43	67.55%	1760.63	65.15%	1941.91	62.66%
Model 3	985.47	81.16%	1154.59	77.15%	1467.96	71.77%

Figure 13 illustrates a graphical summary of the total logistics cost of the three models with respect to the geographical dispersion of customers.

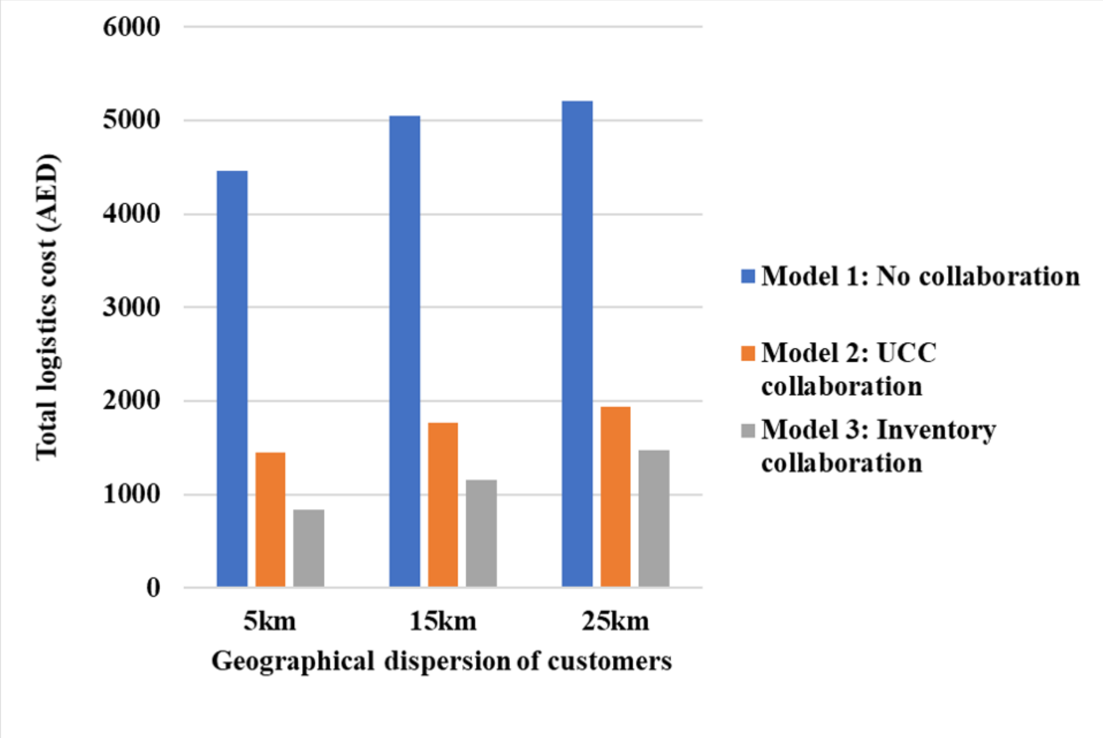


Figure 13: Total logistics cost vs geographical dispersion of customers for all distribution strategies proposed

For the first case (5 km geographical dispersion), the minimum cost associated with the first model considering no collaboration was determined as AED 4458.04. However, the optimal value for the cost function in the second model employing UCC collaboration was found to be AED 1446.43, resulting in savings of 67.55% with respect to the first model. Likewise, the minimum cost for the third model with inventory collaboration was obtained as AED 985.47 with savings of 81.16% as compared to the first model.

In the second case (15 km geographical dispersion), the minimum logistics cost associated with the Model 1 considering no collaboration was determined as AED 5052.44. The optimal value for the cost function for the second model was found to be AED 1760.63, resulting in a 65.15% savings as compared to the first model. In the same way, Model 3 involving inventory collaboration was obtained as AED 1154.59 with a savings of 77.15% as compared to the first model.

Finally, for a 25 km geographical dispersion of customers, that the minimum logistics cost associated with the Model 1 considering no collaboration was determined as AED 5200.4. The optimal value for the cost function for the second model was found to be AED 1941.91, resulting in a 62.66% savings as compared to the first model. In the same way, Model 3 involving inventory collaboration was obtained as AED 1467.96 with a savings of 71.77% as compared to the first model.

From the results above, we gather the following conclusions:

It was found that Model 1 incorporating no collaboration yielded the maximum cost in all the cases simulated with respect to customer dispersion. The unreasonably high cost is due to the assumption that every customer in the network must be fulfilled by the depot receiving the order, no matter how far the customer is located. This led to a huge transportation cost incurred by the respective depots. A more realistic cost could be attained by relaxing this assumption, and adding a penalty cost for not fulfilling a customer. However, maintaining the strict assumption was mandatory for a fair comparison between the models proposed. That being said, the network used in Model 1 is typical of those with a small startup having local customers, and as the company expands into a bigger geographical market, the no-collaboration strategy will result in unsustainably high costs. An underlying assumption for all models is that there is always enough inventory of the unique product in their respective depots to satisfy all customers in the network. Moreover, since the customer demands are being fulfilled by the respective depots themselves, forecasting of customer demands is not essential for this model.

Secondly, it was observed that Model 2 employing UCC level collaboration yielded a much lower total logistics cost with an average savings of about 65.12% as compared to Model 1. This model represents a network collaboration among 3PL providers, where the fulfillment of customers can be shared among the 3PL providers. Rather than the UCC having to fulfil the demands of random depots to the customers, the network will allow the flexibility of fulfilling any customer through any UCC. Moreover, the strength of this model stems from the pooling of different unique products into UCCs, thereby fulfilling the demands of different customers jointly. This kind of a network is relatively unsophisticated to generate, due to the fact that the collaboration takes places among 3PL providers rather than the depots themselves. Consequently, the information sharing takes place among the 3PL providers rather than the depots themselves, and therefore, a low level of trust is sufficient to produce such a model.

Lastly, Model 3 incorporates inventory and distribution collaboration among the depots, resulting in a much more flexible network. This model represents a network having horizontal collaboration among the depots, resulting in a much lower overall logistics cost with a savings of around 76.70% compared to the model encompassing no collaboration. Moreover, it was observed that this model outperformed the model encompassing UCC level of collaboration by a significant proportion in all the datasets considered. This is due to the fact that horizontal collaboration of inventory allows a more distributed network with barely any added fixed cost, leading to a more flexible network. Furthermore, with all costs considered, the model gave the optimal solution such that the customer is fulfilled by the nearest warehouse. The results for this model conclude that the location of the warehouses is one of the most crucial element in logistics cost, and inventory collaboration allows for a more dispersed network with hardly any fixed cost. Therefore, this analysis reinforces our assumption that the model depicting inventory collaboration within the depots will result in the least cost.

Chapter 4. Variable Neighborhood Search Algorithm for the Proposed Inventory Collaboration Model

Modeling of complex issues often leads to NP-hard problems, and real-life distribution problems in logistics and Supply Chain Management are often medium - to - large size problems. However, the large set of tools now available to solve for exact solutions (branch- and- bound, cutting planes, column generation etc.) may not be able to solve large set of instances, and thus one reverts to heuristics and metaheuristics. In this chapter, a Variable Neighborhood Search Algorithm (VNS) is implemented to find near optimal solutions for the proposed mathematical model. The developed algorithm is proposed to minimize the total logistics cost of the network, whilst satisfying all constraints for the model taken in consideration. The proposed algorithm was validated by comparing the solutions obtained from GAMS, and are discussed in the coming section.

4.1. Variable Neighborhood Search (VNS)

Variable Neighborhood Search (VNS) is a recently developed metaheuristic based on the principle of systematic change of neighborhood during the search, in order to avoid poor local optima by exploring between solution spaces. The algorithm repeatedly applies local search methods to get the local optima from the neighborhood solutions, and solves iteratively until no further improvements can be made or a stopping condition is met. The algorithm exploits the idea of local search and neighborhood change, and relies on the following observations:

- The local minima for a neighborhood structure is not necessarily an optimal with respect to another neighborhood.
- The global minima has to be the local minima with respect to all neighborhood structures.
- Since the value to be minimized remains the same for all the neighborhood structures, the local minima with respect to one or several neighborhoods are relatively close to each other.

This last observation, which is empirical, implies that a local optimum often provides some information about the global one. This may for instance be several variables with the same value in both. However, it is usually not known which ones are such. The main advantage of VNS in addition to providing good solutions is its simplicity and interpretability, as the algorithm is built up of simple logical neighborhoods. The algorithm can hence provide a good insight on how the solution was found, which in turn can lead to more efficient and sophisticated implementations.

The algorithm illustrated in Figure 14 explains the general idea of the general Variable Neighborhood Search Algorithm. The process comprises of three main steps; shaking or diversification, local search or intensification, and evaluation. The first step would be to identify a set of neighborhood structures N_k (k=1,. . . ,k_{max}) , which creates k solution spaces for the problem. Once the initial solution is generated, an appropriate stopping condition is identified. The algorithm then starts with the first pre-specified neighborhood structure (k = 1) to generate another solution x' using the initial solution. The idea of the shaking phase is to diversify the search through making several random moves to escape from local optima. With the generated solution x', the algorithm seeks an to find the best possible solution x" in that neighborhood using the local searches defined. This solution is then evaluated and accepted only if an improvement has been made compared to the current solution. If no better solutions are found in that neighborhood, the algorithm then moves to the next neighborhood with the current solution and the whole process repeats until the stopping condition is reached.

Initializations. Select the set of neighbourhood structures $N_k, k = 1, \dots, k_{max}$, that will be used in the search; find an initial solution x; choose a stopping condition;
Repeat the following until the stopping condition is met:
(1) Set $k \leftarrow 1$;
(2) Until $k = k_{max}$, repeat the following steps:
  (a) Shaking. Generate x' at random from the k^{th} neighborhood of x ($x' \in N_k(x)$);
  (b) Local search. Apply some local search method with x' as initial solution; denote with x'' the so obtained local optimum;
  (c) Move or not. If this local optimum is better than the incumbent, move there ($x \leftarrow x''$) , and continue the search with N_1 ($k \leftarrow 1$); otherwise, set ($k \leftarrow k + 1$);

Figure 14: Steps of the basic VNS

Studies suggest that the basic VNS can be improved by applying a deterministic change of neighborhoods, from which the concept of Variable Neighborhood Descent (VND) was introduced. The idea of VND is that the algorithm explores pre-specified neighborhood structures until a local optimum for all considered neighborhoods is reached, and this can simply be achieved by going over all neighborhood structures once a better solution is found. The VND algorithm is illustrated in Figure 15.

Initializations. Select the set of neighborhood structures $N'_k, k = 1, \ldots, k'_{max}$, that will be used in the descent; find an initial solution x;
Repeat the following until no improvement is obtained:
(1) Set $k \leftarrow 1$;
(2) Until $k = k'_{max}$, repeat the following steps:
(a) Exploration of neighborhood. Find the best neighbor x' of x $(x' \in N'_k(x))$;
(b) Move or not. If the solution thus obtained x' is better than this local optimum is better than x, set $x \leftarrow x'$; otherwise, set $k \leftarrow k+1$;

Figure 15: Steps of the basic VND

In this thesis, a VNS algorithm was implemented that uses the VND in the local search phase. The aforementioned algorithm is illustrated in Figure 16.

Initializations. Select the set of neighborhood structures $N_k, k = 1, \ldots, k_{max}$, that will be used in the shaking phase, and the set of neighborhood structures $N_l, l = 1, \ldots, l_{max}$ that will be used in the local search; find an initial solution x; choose a stopping condition;
Repeat the following sequence until the stopping condition is met:
(1) Set $k \leftarrow 1$;
(2) ***Repeat*** the following steps until $k = k_{max}$:
(a) Shaking. Generate x' at random from the k^{th} neighborhood of x $(x' \in N_k(x))$;
(b) Local search by VND.
(b1) Set $l \leftarrow 1$;
(b2) ***Repeat*** the following steps until $l = l_{max}$:
Exploration of neighborhood. Find the best neighbor x'' of x' in $N_l(x')$;
Move or not. If $f(x'') < f(x')$ set $x' \leftarrow x''$ and $l \leftarrow 1$; otherwise set $l \leftarrow l+1$;
(c) Move or not. If the local optimum x'' is better than the incumbent, move there $(x \leftarrow x'')$, and continue the search with N_1 $(k \leftarrow 1)$; otherwise, set $(k \leftarrow k+1)$;

Figure 16: VNS Algorithm with VND

4.2. VNS Implementation for the Proposed Inventory Collaboration Model

Before the methodology is described, we must first define the neighborhood structures for the shaking phase and the local search phase for our model. In our implementation of the VNS, three neighborhood structures are defined, denoted by N_k, where k = 1, 2, 3. Also, one local search phase is defined for the model, denoted by L_1. For the shaking phase, the neighborhood structures are as follows:

- Neighborhood N_1 (k=1): Select two depots randomly, select a customer randomly from each of the selected depot and swap the customers
- Neighborhood N_2 (k=2): Select one depot randomly, select two customers randomly from the selected depot and swap the customers.
- Neighborhood N_3 (k=3): Select two depots randomly, select one customer randomly in the first depot and move it into the second depot.

The following local search will be conducted on all the neighborhood structures:

- Local Search L_1 (l = 1): For a given combination of vehicle and depot, explore the different arrangement of customers by swapping their positions to generate different transportation routes.

Now that the neighborhoods and the local search phases have been briefly defined, we must first refresh ourselves with the sequence of operations for the model in consideration before describing the methodology for the implementation of the VNS. These operations are summarized in the Table 16.

Table 16: Proposed structure to solve the model using sequential approach

Time Period	**Operation**	**Cost**
$T = 0$	• Line-haul transportation based on forecasted demand	• Line-haul transportation cost
T = 1, 2, 3, 4	• Fulfil customers' demands through last-mile delivery from the depot to the customer using capacitated vehicles • Calculate leftover inventory after fulfilment of customers in current time period	• Last-mile transportation cost • Inventory holding cost

It is to be noted that from herein after, the time periods will be denoted by T, where T ranges from $T = \{0, 1, 2, 3, 4\}$. Time period $T = 0$ is the initial time period where the line-haul transportation takes place, and the following time periods are when the customer demands will be satisfied sequentially. Based on the literature discussed earlier, the structure for the VNS algorithm for our proposed mathematical model was modeled and implemented, and is illustrated in Figure 17.

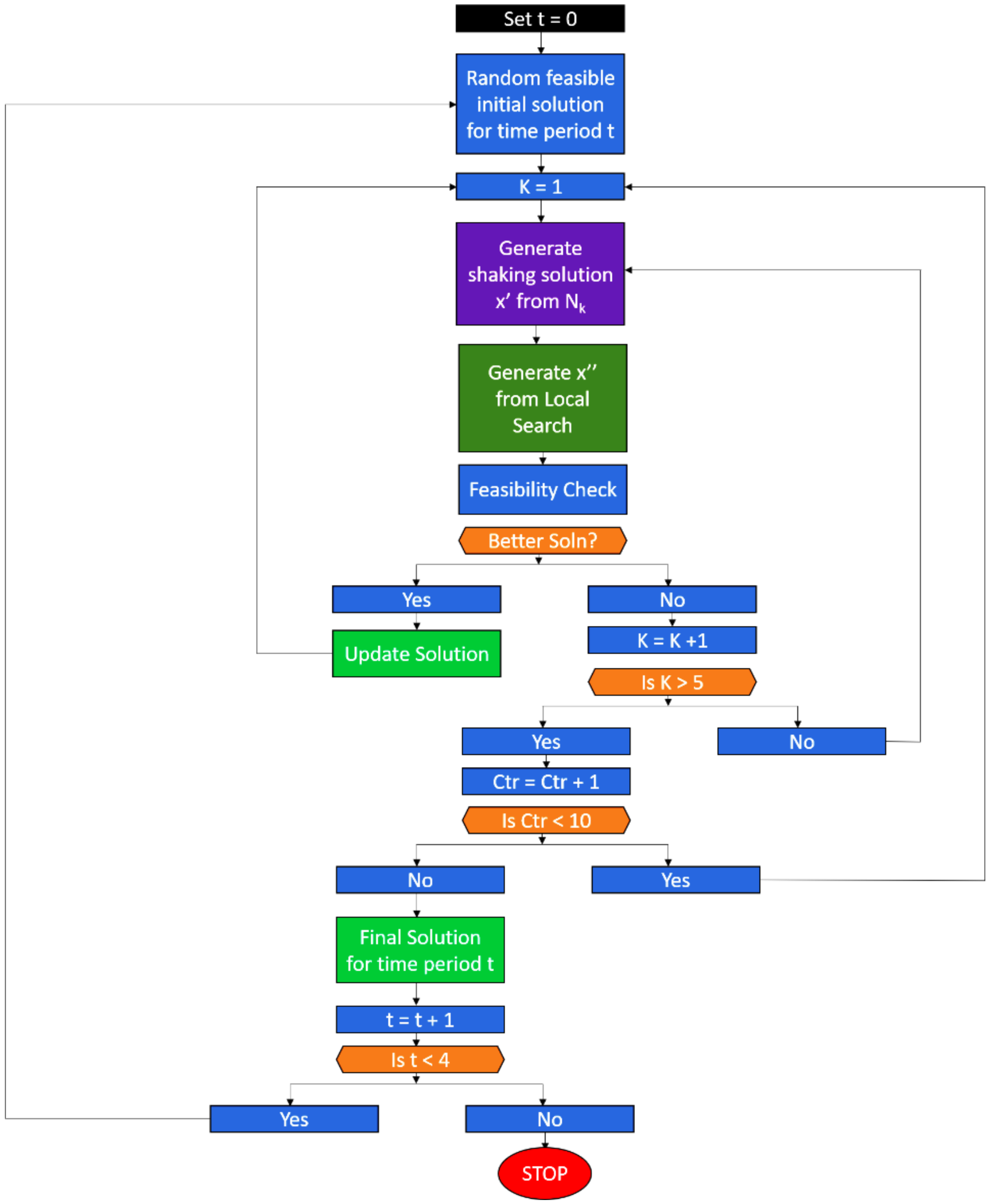


Figure 17: A flowchart representation of the implemented VNS algorithm

The first step would be to construct a feasible initial solution starting from time period $T = 1$. Once a solution is generated, it passes through the neighborhood structure N_1 to shake the existing solution. If found, the shaked solution goes through the local search L_1 and then checked for feasibility. If a better solution was found, the existing best solution gets updated and K gets set to 1 again, meaning that the new-found solution is passed through all neighborhoods again starting from N_1. If a better solution is not found using N_1, the solution is passed through the next neighborhood structure, for which the same sequence of operations occurs. However, if the best-found solution has been shaked through all the neighborhoods, and still no better solution was found, the solution is fed back to the neighborhoods starting from N_1. This sequence of operations is looped for a preset number of iterations, which is denoted by *ctr*. The result of all these operations conducted will produce the best-found solution for the first time period $T = 1$, and hence this entire procedure will be done a total of four times, one for each of the time periods considered.

Keeping in mind the sequence of operations earlier described, this section is organized as follows. First, the procedure to generate a feasible initial solution will be described in detail. Secondly, the operations required to check the feasibility of a solution will be explained, and then all the cost calculations will be clarified upon. Lastly, the neighborhood and local searches for our implementation of the VNS will be discussed in detail.

4.2.1. Initial solution. The following steps need to be conducted in order to attain a solution for a single time period:

1. Calculate the total available inventory supply after line-haul transportation based on forecasted demands and initial supply of inventory at the depots
2. Assign all the customers in the network to the depots, whilst satisfying the supply and demand constraints
3. Generate the solution by routing of the capacitated vehicles

4.2.1.1. Line-haul transportation. At time period $T = 0$, the line-haul transportation is undertaken between the depots according to the forecasted customers' demands for the entire month. The expected demands are forecasted on a monthly basis for each city (denoted by depots *D1*, *D2* and *D3*) and for each unique product. Since each of these depots have an initial inventory, line-haul transportation will only occur if the initial supply of products in the required depot is less than the expected demand of the product for that depot. Figure 18 illustrates the line-haul transportation, and the closing inventory supply calculations.

Supply (T = 0)			
	P1	P2	P3
D1	500	-	-
D2	-	500	-
D3	-	-	500

+

Expected Demand			
	P1	P2	P3
D1	25	35	20
D2	15	35	20
D3	20	15	50

=

Supply (T = 1)			
	P1	P2	P3
D1	465	35	20
D2	15	450	20
D3	20	15	460

Figure 18: Calculation of closing inventory quantities after line-haul transportation

4.2.1.2. Customer allocation to the depots. Now that the depots have the necessary inventory to satisfy customer demands of different product types, one can look into finding a feasible initial solution. Since the problem description allows any customer to be satisfied by any depot, given that the depot has enough available supply of the required product to satisfy the customer's demand; a random procedure is first used to build feasible customer allocations to the depots. An example of 3 depots and 15 customer nodes will be used, where the depots are represented by *D1*, *D2* and *D3*, whereas the customers are represented by *C1*, *C2*, up to *C15*.

Since the depots and customers are numbered, we can simply use this order to build an initial solution. Starting from time period $T = 1$, customer *C1* is first selected, followed by a depot selected at random, and if the depot has enough inventory to satisfy customer *C1*, the customer will be linked to the depot. If the depot does not have the inventory required to satisfy the customer, the customer is satisfied by the original depot (the depot having infinite supply of that unique product). Once the customer is linked to the depot, the available supply for that depot is deducted by the demand of the customer in that time period. This step is repeated for all customers to attain a feasible initial allocation of customers to the depots for a single time period. Since the structure of the solution will be the same for all time periods, all the examples and illustrations will be provided for only a single time period for convenience of explanation as shown in Figure 19.

Customer Allocation (T = 1)						
D1	C4	C6	C10	C13		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C11	C12	C14

Figure 19: Generated customer allocation matrix

Since this approach uses the numbered order of the customers, it will inevitably prioritize the customers which have been allocated first. The result of this step identifies the customers that are allocated to each depot.

Algorithm 1 Customer allocations for time period (t)

Inputs: Available supply after line-haul transportation, actual demand of customers, time period (t)
Outputs: Inventory at time period (t), customer allocation matrix at time period (t)
Initial inventory = Get initial supply
Initialize inventory (t+1) = Remaining inventory (t)
for all (i in $CUSTOMERS$) **do**
  for all (j in $DEPOTS$) **do**
    if (Inventory at depot j) $>$(Demand at customer i) **then**
      index = depot j which has the minimum distance to customer i
    else
      index = original depot
    end if
    Inventory (t + 1) = Update inventory of depot j
  end for
end for

For example, it can be seen that depot *D1* will satisfy the demands of customers *C4*, *C6*, *C10* and *C13* in time period $T = 1$. Since all the customer and depot node locations are predetermined, a better approach of allocating customers to the depots would be based on proximity. Taking customer *C1* as an example, first check all the distances from customer *C1* to the depots *D1*, *D2* and *D3*, and allocate the customer to the closest depot, given that the depot has enough inventory to fulfil the customers demand. If the closest depot does not have the inventory to satisfy the customers' demand, the customer can be assigned to its original depot (the depot which has infinite supply of the unique product which is demanded). This will lead to a much better initial allocation of customers, which immensely reduce the number of iterations required to solve the model. Therefore, this approach was used to allocate the customers to the depots, and is illustrated in Algorithm 1.

The scenario considered consists of four time periods, with the assumption that the remaining inventory of the last time period is the available supply of the current time period. Therefore, the entire process described is repeated four times to get a feasible customer allocation to the depots for all the time periods considered.

Demand Calculations:

Once the customers are allocated to each of the depots, the demands of the products from each depot can be calculated using the subroutine illustrated in Algorithm 2. The demand matrix calculated for the depots based on each product is illustrated in Figure 20

Algorithm 2 Demand allocations for time period (t)

```
Inputs: Customer allocation matrix at time period (t), actual demand of customers,
time period (t)
Outputs: Demand allocation matrix
Initialize demand = 0
for all (i in DEPOTS) do
   for all (j in customerlength[i]) do
      temp = allocate customer
      for all (k in DEPOTS) do
         demand of product k += customerdemand[temp-DEPOTS][k]
      end for
   end for
end for
```

Demand (T = 1)			
	P1	P2	P3
D1	0	34	0
D2	28	15	0
D3	5	12	35

Figure 20: Generated customer demand matrix

4.2.1.3. Vehicle Routing. Although the customer allocation is a critical aspect, the initial solution itself requires much more information. By this point, we have assigned all customers to their respective depots. In order to attain a solution, capacitated vehicles need to be routed to and from the depots to their respective customers. Figure 19 shows the structure of the customer allocation, in which 15 customers' requests " C_1 to C_{15}" are to be satisfied from 3 depots " D_1 to D_3". After the customers are assigned to the depots, a feasible initial solution is generated as illustrated in Figure 21. Each row denotes a vehicle, in which the route starts from a depot and satisfies some customers and comes back to the depot.

Initial Solution (T = 1)				
Veh #1	D1	C4	C6	
Veh #2	D1	C10	C13	
Veh #3	D2	C1	C3	C8
Veh #4	D2	C9	C15	
Veh #5	D3	C2	C5	
Veh #6	D3	C7	C11	C12
Veh #7	D3	C14		

Figure 21: Generated a feasible solution using the customer allocation matrix

For example, the route of vehicle 1 can be read as *D1-C4-C6-D1*. It can also be noticed that two vehicles are being used to fulfil the customers' assigned to depot *D1*, because of the vehicle capacity constraint. Algorithm 3 explains the generation of the vehicle routes using the customer allocation matrix earlier generated.

Algorithm 3 Generate vehicle allocation of customers for time period (t)

```
Inputs: demand allocation matrix, actual demand of customers, Available supply
after line-haul transportation, actual demand of customers, time period (t)
Outputs: customer-vehicle allocation at time period (t), tripcount, vehiclecount
Initialize tripmatrix = 0, vehiclecount = 0, tripcount = 0
for all (k in vehicles) do
    tripmatrix[0] = corresponding depot number
    if (All customers are not assigned to vehicles) then
        for all (j in customerlength[depotnumber]) do
            if (vehiclecap[vehiclecount]) >(customerdemand) then
                Assign customer to the vehicle
                Decrease vehiclecap[vehiclecount]
            else
                vehiclecount++
            end if
        end for
    end if
end for
```

From hereinafter, the same structure of the customer allocation and vehicle routing solution as shown in Figure 19 and Figure 21 will be used to explain the phases of the implemented VNS.

4.2.2. Feasibility check.

There are quite a few things that need to be verified in order to determine if the solution produced is feasible, and they are as follows:

- The available inventory in the depots are enough to satisfy the allocated customers for all time periods
- The total demand matrix, which comprises of the demand of each product for every depot is calculated correctly
- The current inventory is calculated as the leftover inventory from the previous time period
- All the customers are satisfied for all time periods
- A customer can be served by only one vehicle in a time period
- The orders of the customers satisfied by a certain vehicle constitutes the load of that vehicle, where the load must not exceed the capacity of the vehicle
- The vehicle can only leave from a depot and has to come back to the same depot

4.2.3. Cost calculations.

In this section, the detailed cost calculations for the network in consideration is explored. Three types of costs were considered to determine the total logistics cost of the network, namely the line-haul transportation cost, last-mile transportation cost and the inventory holding cost.

Line-haul transportation cost: The total line-haul cost for the network can be calculated directly from the line-haul transportation, assuming a full-truckload collaboration and is already explained in section 4.2.1.1. Note that the line-haul cost calculated is solely a function of the distance travelled.

Last-mile transportation cost: The total last-mile cost for the four time periods in consideration can be calculated using the solution set that involves routing of the vehicles, from which one can determine the route of each vehicle and the customers served. Once the routing of the vehicles are determined, the last-mile costs can be found simply as a function of the distance travelled. The subroutine in Algorithm 4 clarifies the detailed cost calculation for the last-mile.

Algorithm 4 Last-mile trip cost for time period (t)

Inputs: Customer-trip matrix at time period (t), available , vehiclecount, tripcount, time period (t)
Outputs: overalldistance
Initialize overalldistance = 0
for all (i in $vehiclecount$) **do**
  for all (j in $tripcount[i]$) **do**
    overalldistance+= distance of route (from the routing solution)
  end for
end for

Inventory holding cost: Since the leftover inventory is carried over the next time period, the total holding cost can be determined from the available supply and demand for all the time periods. The inventory holding cost for a single time period is product of the leftover inventory of the depots and the unit inventory holding cost. Therefore, the total inventory holding cost is essentially the summation of the inventory holding cost for all the time periods. The subroutine in Algorithm 5 illustrates the holding cost calculation for a single time period.

Algorithm 5 Total inventory holding cost

Inputs: Available inventory at all time periods
Initialize inventorycost = 0
for all (t in TP) **do**
  for all (i in $DEPOTS$) **do**
    for all (j in $DEPOTS$) **do**
      if (i == j) **then**
        if (inv[i][j][t + 1] $>$0) **then**
          totalinventory += inv[i][j][t];
        end if
      end if
    end for
  end for
end for
inventorycost = totalinventory * inventoryholdingcost

4.2.4. Neighborhood and local searches.

In this phase, several random changes from one neighbour structure to other neighbour structure are performed to escape from local search local optima, which is known as ‘shaking’. The three-implemented different neighbourhood structures are as follows:

4.2.4.1. Neighborhood Structure N_1 (k=1). The first neighbourhood structure in the shaking phase is to select two customers randomly from each of the selected depot and swap the customers. Since there are supply, demand and capacity constraints, not all customers can be swapped for the depots considered. A sequence of steps was carried out to define this neighbourhood shake, and they are as follows:

- Two depots were selected at random, with the condition that these depots at least serve one customer. The algorithm will continue to find two depots which satisfy the condition mentioned, or the algorithm moves to the next neighbourhood based on a pre-defined stopping condition.
- For the depots selected, the customers were chosen at random, and these customers will only be swapped if there is enough available supply at the depots to satisfy these different set of customers. If not, the algorithm looks for another set of customers, or stop according to a stopping condition based on the number of iterations.
- The customers are then swapped to create a new feasible solution and the available supply at the depots for each product type is updated.

Before neighborhood shake:

Customer Allocation (T = 1)						
D1	C4	C6	C10	C13		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C11	C12	C14

After neighborhood shake:

Customer Allocation (T = 1)						
D1	C4	C11	C10	C13		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C6	C12	C14

Figure 22: Demonstration of the shaking phase for neighborhood 1

As it can be seen from Figure 22, the depots *D1* and *D3* were chosen at random, followed by a random selection of customers *C6* and *C11* in the depots *D1* and *D3* respectively. Since the available supply at *D3* and *D1* was enough to satisfy customer *C6* and *C11* respectively, the algorithm swaps these two customers which creates a new feasible customer allocation of the depots. Using this customer allocation, the new solution can be found by simply routing the customers through the vehicles. The subroutine in Algorithm 6 explores the aforementioned neighbourhood shake.

4.2.4.2. Neighborhood Structure N_2 (k=2). The second neighbourhood phase involves selection of one depot randomly, from which two customers are selected randomly and swapped if possible. In this case, there are vehicle capacity constraints, and therefore not all customers randomly selected can be swapped. A sequence of steps was carried out to define this neighbourhood shake, and they are as follows:

- A depot selected at random must have at least a minimum of two customers allocated to them, since this neighborhood involves swapping two customers from the same depot. Therefore, the algorithm will continue to randomly find a depot such that the depot has at least two customers assigned to it.
- For the depot thereby selected, two customers are selected at random, and inspected for feasibility. For this neighborhood, since the customers are swapped from the same depot, the only feasibility constraint is coming from the capacity of vehicles. If this condition is satisfied, the two customers are swapped to generate a new feasible solution. Figure 23 illustrates the utility of the second neighbourhood structure with a simple example.

Algorithm 6 Select two depots randomly, select a customer randomly from each of the selected depot and swap the customers for time period (t)

Inputs: Customer allocation matrix at time period (t), actual demand of customers, Available supply at time period (t), time period (t)
Outputs: Updated customer allocation matrix at time period (t)
randa, randd = select two random depots
while (randd == randa) **do**
  select randd
end while
randb, randc = select two random locations in depot randa and randd respectively
Calculate demand of customer randb in depot randa
while (Inventory[randd] >demand[randb]) OR (Inventory[randa] >demand[randc]) **do**
  Calculate feasible randa, randb, randc and randd
end while
Check feasibility
Swap customer randb and randc from depot randa and depot randd respectively
Keep the rest of the customer allocation arrangement as is

Before neighborhood shake:

Customer Allocation (T = 1)						
D1	C4	C6	C10	C13		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C11	C12	C14

After neighborhood shake:

Customer Allocation (T = 1)						
D1	C13	C6	C10	C4		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C11	C12	C14

Figure 23: Demonstration of the shaking phase for neighborhood 2

It was found that depot *D1* has two vehicles leaving the depot to satisfy all its customers and the routes originally formed were *D1-C4-C6-D1* and *D1-C10-C13-D1*. The algorithm chose depot *D1* at random, and then randomly selected customers *C4* and *C13* from depot *D1*. Since the two vehicles had enough capacity to swaps the customers, the algorithm continues and therefore a new routing solution is now generated. After finding a new feasible solution, the available supply at each depot for each product type and the demand matrix for each city is updated. The subroutine in Algorithm 7 details the aforementioned neighbourhood shake.

Algorithm 7 Select one depot randomly, select two customers randomly from the selected depot and swap the customers for time period (t)

Inputs: Customer allocation matrix at time period (t), time period (t)
Outputs: Updated customer allocation matrix at time period (t)
randa = select a random depot
randb, randc = select two random customers in depot randa
Check feasibility
Swap customer randb with customer randc
Keep the rest of the customer allocation arrangement as is

4.2.4.3. Neighborhood Structure N_3 (k=3). In this neighbourhood structure, we select two depots randomly, select one customer randomly in the first depot and move it into the second depot. Therefore, a crucial step would be to make sure that the first depot selected has at least one customer assigned to it, and the second depot needs to be selected such that it can fulfil the demands of this randomly chosen customer from the first depot. Feasibility check for several constraints will be required due to changes in inventory supply, the demand matrix and the capacity of the vehicles. The utility of this neighborhood is explained using Figure 24.

Before neighborhood shake:

Customer Allocation (T = 1)						
D1	C4	C6	C10	C13		
D2	C1	C3	C8	C9	C15	
D3	C2	C5	C7	C11	C12	C14

After neighborhood shake:

Customer Allocation (T = 1)						
D1	C4	C6	C10	C3	C13	
D2	C1	C8	C9	C15		
D3	C2	C5	C7	C11	C12	C14

Figure 24: Demonstration of the shaking phase for neighborhood 3

The depots *D1* and *D2* were chosen randomly, such that *D2* had at least one customer assigned to it. Furthermore, customer *C3* was randomly chosen from depot D2 and the position of customer *C13* was chosen from depot D2 by the algorithm. Since, *D1* has the available inventory to satisfy customer *C3*, the algorithm continues and reassigns customer *C3* in depot *D1*, thus creating a new customer allocation. After creating a new feasible solution using this neighborhood, the available supply at each depot for each product type and the demand matrix for each city is updated. The subroutine for this neighbourhood can be found in Algorithm 8.

Algorithm 8 Move a customer from one depot to another for time period (t)

Inputs: Customer allocation matrix at time period (t), actual demand of customers, Available supply at time period (t), time period (t)
Outputs: Updated customer allocation matrix at time period (t)
Move a customer from depot = randa to depot = randd
randa, randd = select two random depots
while (randd == randa) **do**
  select randd
end while
randb, randc = select two random locations in depot randa and randd respectively
Calculate demand of customer randb in depot randa
while (Available inventory[randd] >demand[randb]) **do**
  Calculate feasible randa, randb, randc and randd
end while
Check feasibility
Move customer randb from depot randa to depot randd
Keep the rest of the customer allocation arrangement as is

The routing of vehicles is conducted on the customer allocation matrix generated by the neighbourhoods, followed by the local search (l = 1) to determine the best possible set of routes for this new solution.

4.2.4.4. Local Search L_1 (l = 1). For a given combination of vehicle and depot, the local search neighborhood structure explores the different arrangement of customers by swapping their positions to generate different transportation routes. This involves an exhaustive swapping of customers within their respective depot to find the best possible sequence of the routes. If the new set of routes formed resulted in a lower overall cost, the best-found solution is updated and the algorithm reiterates until no better solution can be found. The local search helps in routing the customers. The subroutine for this local search phase is recorded in Algorithm 9. The overall logistics cost is then found and compared to the current best solution, and if the overall cost of that time period decreases, the solution is updated and the VNS algorithm starts from N_1 (k = 1) again. If a better solution is not found, the algorithm proceeds to the next neighbourhood. The entire VNS implementation is clearly explained in Figure 17, for which the result is the best set of routes for the network proposed.

Algorithm 9 Local search to explore all possible arrangements of customers for a given vehicle and depot for time period (t)

Inputs: Customer-trip matrix at time period (t), distance matrix, vehiclecount, tripcount, time period (t)
Outputs: updated customer-trip matrix
Initialize overalldistance = 0
for all (k in $vehiclecount$) **do**
  for all (i in $tripcount[k]$) **do**
    for all (j in $tripcount[k]$) **do**
      swap customer i and j in vehicle k
      calculate new overall distance
      if (new overall distance <old overall distance) **then**
        update the customer arrangement matrix
      else
        do not update
      end if
    end for
  end for
end for

4.3. VNS Validation

To test the effectiveness of the proposed algorithm and to observe how it behaves in term of computational time when increasing the total number of nodes, several experiments where conducted using random constructed datasets obtained from TSPLIB, which is a public library of sample instances for the Travelling Salesman Problem (TSP). To validate the VNS implementation, the best-found solution from the heuristic can be compared to the proven optimal solution found using GAMS. The algorithm is coded using C++ programming language and all the experiments were conducted using Intel(R) Xeon(R) CPU @ 3.60GHz with 16 GB RAM machine under Windows 10 (64 bit). Table 17 illustrates the results obtained from finding a solution to the proposed model using the VNS algorithm for different number of customer nodes. All data reported for VNS are an average of 10 runs.

Table 17: Elapsed time, GAMS vs VNS

Dataset	Number of customers	GAMS elapsed time (sec)	VNS elapsed time (sec)
icw1483	9	33.2	87.9
	10	85.6	112.8
	11	378.9	146.2
	12	3521.7	167.3

Both GAMS and the heuristic algorithm finds the solution very fast for small number of nodes, however the algorithm performs much faster when the number of nodes is increased as compared to GAMS.

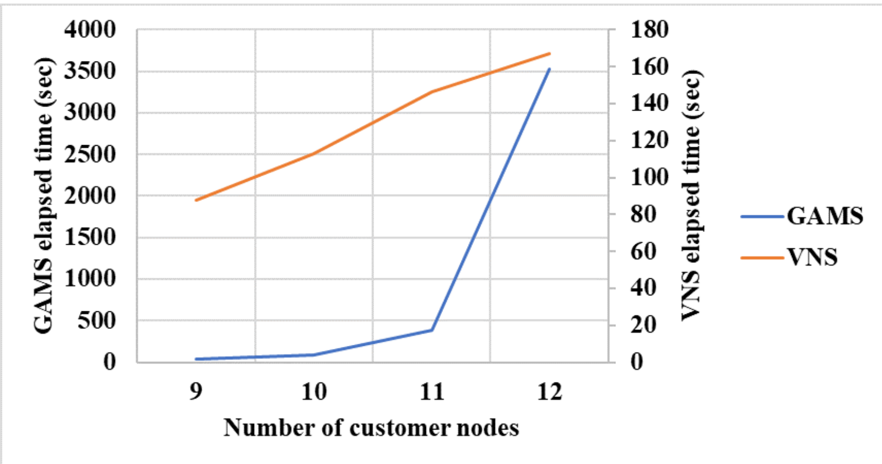


Figure 25: Elapsed time, GAMS vs VNS

It can be seen that GAMS took around 52 minutes to find an optimal solution for 12 customer nodes, whereas VNS took less than 3 minutes to solve the same network.

This can also be observed from Figure 25, which depicts the sharp exponential trend of the time it takes to solve the model using GAMS on increasing customer nodes, compared to the relative linear increase in time taken by the VNS algorithm. Therefore, in terms of time taken to solve the model, VNS algorithm significantly outperforms the GAMS model.

Although the VNS performed better in terms of time, the GAMS provides a proven optimal solution unlike the heuristic algorithm. Therefore, we must compare how the heuristic performed with respect to the optimal solution found using GAMS.

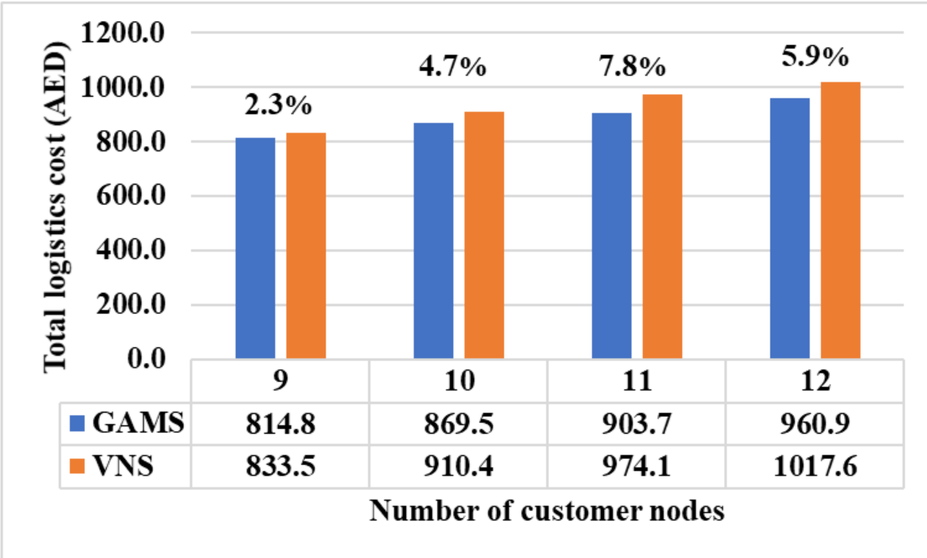


Figure 26: Percentage deviation of VNS solution from the optimal solution by GAMS

It can be seen from Figure 26 that for a network of 9 customers, there was only 2.3% deviation from the optimal solution found using GAMS. Also, since the heuristic solution reported is average of 10 runs, it was observed that the optimal solution was obtained in several of the runs performed. Even upon increasing the customer nodes, the maximum percentage deviation was around 7.8%, which is considered satisfactory. The comparison could not be extended due to the limitations of the GAMS model. Now that the VNS result quality has been validated, we can observe the effectiveness of the heuristic in terms of computational time for medium to large size networks.

Therefore, Figure 27 illustrates the elapsed time of the heuristic on increasing the number of customer nodes in the network. It can be seen that the elapsed time increases upon increasing the customer nodes as expected. For a medium sized problem of 50 customer nodes, the heuristic was able to solve the network within 27 minutes, which is adequate for our purpose. Moreover, even for large network of 90 customer nodes, the heuristic was able to solve it within 52 minutes.

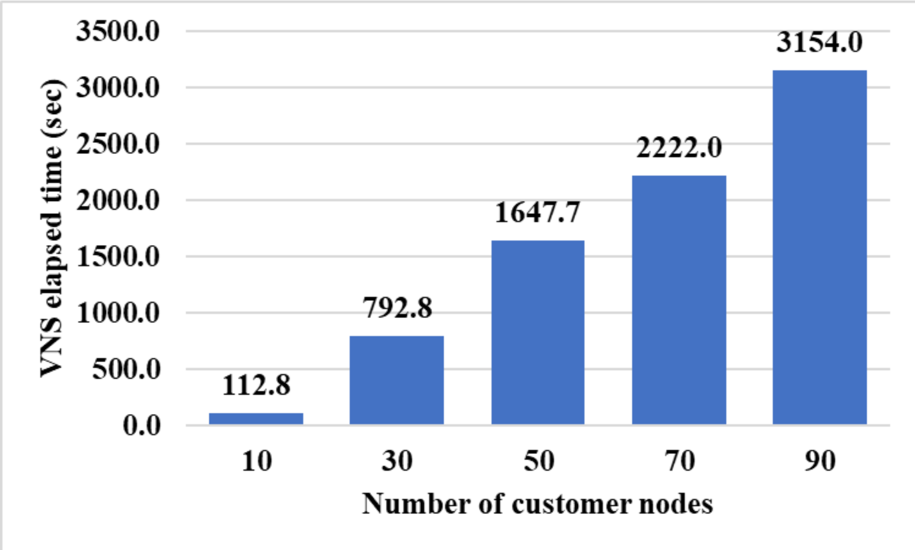


Figure 27: Elapsed time of VNS heuristic on increasing number of customer nodes

It can be seen from Figure 27 above that the elapsed time increases upon increasing the customer nodes as expected. For a medium sized problem of 50 customer nodes, the heuristic was able to solve the network within 27 minutes, which is adequate for our purpose. Moreover, even for large network of 90 customer nodes, the heuristic was able to solve it within 52 minutes. Therefore, it can be concluded that the heuristic produces good quality solutions in a reasonable amount of time, and is able to solve for medium to large sized networks.

Chapter 5. Results and Analysis

5.1. Sensitivity Analysis

Based on the results from the previous chapter, we concluded that Model 3, which corresponds to the strategy of inventory and distribution collaboration among the depots, resulted in the largest cost savings compared to the other models investigated. Therefore, we chose Model 3 to be the focus of further analysis and discussion in this thesis. This chapter is dedicated to the sensitivity analysis we conducted on Model 3. We selected some key input variables, namely the number of customers, the per-unit cost parameters of inventory holding volume and last-mile delivery, unit volume, vehicle capacity as well as the percentage error in forecasted demand. We varied each of these variables one at a time from -100% to 150% deviation from the base case, which is defined in Table 18.

Table 18: Values of key input variables in the base case

Number of customer nodes	9
Inventory holding cost per unit volume	AED 0.05
Unit volume	19 Liters
Last-mile delivery cost per unit	AED 0.4228
Vehicle capacity	25 units per vehicle
% error in forecasted demand	0%

The total logistics cost for the base case is AED 765.20.

5.1.1. Inventory holding cost sensitivity.

Since the inventory holding cost depends upon the inventory cost per unit liter and the volume of each unit, each of these independent variables were varied to observe the effect in total logistics cost. Table 19 shows how the total logistics cost and its components are affected by the change in inventory cost per liter compared to the base case. When the deviation was -100%, the inventory holding cost per liter was AED 0, and therefore there was no inventory holding cost. Upon increasing the inventory cost per liter, the total logistics cost went up as expected. However, when the percent deviation in holding cost per liter increased from 50% to 100%, the line-haul costs and the inventory holding costs went down to zero. At such a high inventory holding cost per liter, it became more cost efficient for the depots to directly fulfil the end customers rather than store their products at other depots. Therefore, we can conclude that essentially Model 3 (the inventory collaboration model) switches to Model 1 (no collaboration model) when depots find it cheaper not to collaborate.

Table 19: Sensitivity analysis: Variation of inventory cost / liter

Deviation	**Line-haul cost (AED)**	**Last-mile cost (AED)**	**Inventory holding Cost (AED)**	**Total logistics cost (AED)**
-100%	426.6	236.0	0	662.6
-50%	426.6	236.0	51.3	713.9
0%	426.6	236.0	102.6	765.20
50%	426.6	236.0	153.9	816.5
100%	834.14	0	0	834.14
150%	834.14	0	0	834.14

In the context of one-way sensitivity analysis, the inventory holding cost is a linear function of the volume of each unit, therefore the output was just as sensitive to this parameter as it was to the inventory cost per liter. Note that any deviation above 100% has no effect on the total logistics cost, as can be seen from Figure 28.

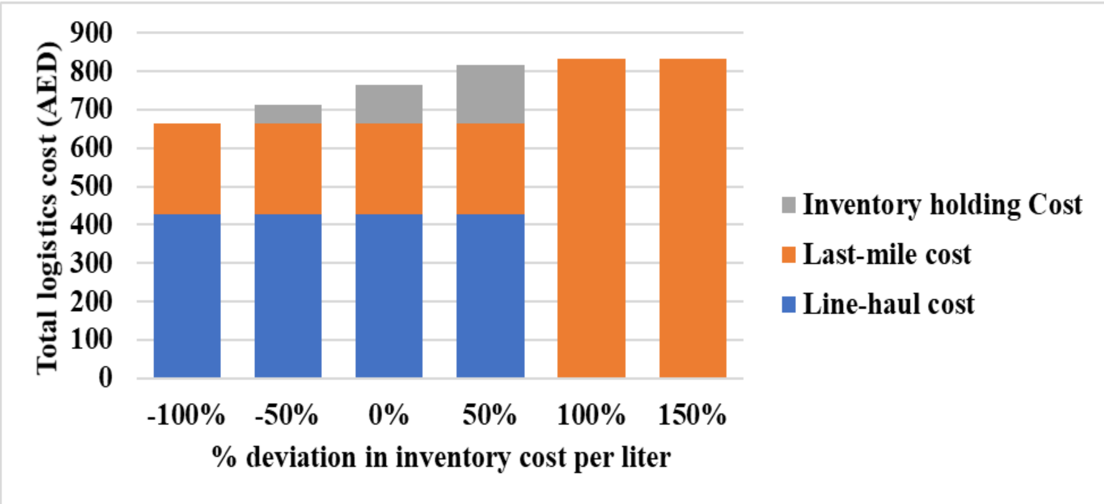


Figure 28: Sensitivity analysis: Variation of inventory cost / liter

5.1.2. Number of customer nodes. In this section, the number of customers in the network were varied to observe the effect on total logistics cost. The Table 20 shows how the total logistics cost and its components are affected by the change in number of customer nodes compared to the base case.

Table 20: Sensitivity analysis: Number of customer nodes

Deviation	Line-haul cost (AED)	Last-mile cost (AED)	Inventory holding Cost (AED)	Total logistics cost (AED)
-50%	287.4	206.8	67.8	562
0%	426.6	236	102.6	765.2
50%	426.6	391.22	233.6	1051.42
100%	426.6	473.74	327.2	1227.54
150%	426.6	587.64	462.6	1476.84

From Figure 29, it can be seen that for a non-zero number of customers, the total logistics cost increases almost linearly with the increase in the number of customers. This observation can be validated by plotting a linear trendline, and an R^2 (coefficient of determination) of 0.997 indicates a high quality fit to the data.

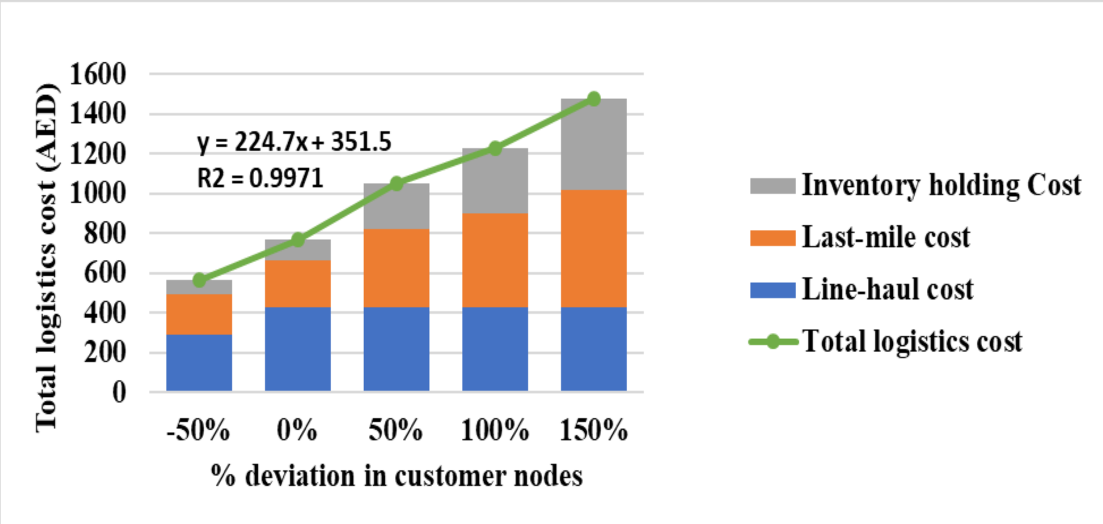


Figure 29: Sensitivity analysis: Number of customer nodes

5.1.3. Error in forecasted demand.

In this subsection, the effect of accurately forecasting demand on the total logistics cost will be studied. The error in this case is the difference between the real demand and the forecasted demand. The real demands of all the 4 weeks in consideration is accumulated, which will be denoted by the forecasted demand with 0% error, and this will be the base case. In other words, if the aggregated real demands are exactly the same as the forecasted demand, the deviation is said to be 0%. The other values simply represent the percent change in the forecasted values from the base case, as calculated for the other parameters. The results for this analysis are reported in Table 21.

Table 21: Sensitivity analysis: Error in forecasted demand

Deviation	Line-haul cost (AED)	Last-mile cost (AED)	Inventory holding Cost (AED)	Total logistics cost (AED)
-100%	0	2880.51	0	2880.51
-50%	426.6	1688.6	34.2	2149.4
0%	426.6	236.0	102.6	765.20
50%	426.6	236.0	239.4	902
100%	426.6	236.0	376.2	1038.8
150%	426.6	236.0	513	1175.6

Since a -100% deviation from the base case implies that there is no forecasted demand, this case would result in the same solution as that observed by the distribution strategy of Model 1. Therefore, for a -100% deviation, the total logistics cost comprises only of the last-mile delivery cost. Moreover, upon increasing the forecasted demand, the inventory holding cost consistently increases, whereas the line-haul cost remains a constant. This is because the line-haul cost is calculated based on a full-truckload delivery, and therefore the delivery cost does not depend on the number of units shipped. On the other hand, the last-mile cost sharply decreases on increasing the forecasted demand, however, the last-mile cost remains constant after a deviation of 0%, i.e. when the real demand is equal to the forecasted demand.

Since all the various cost components are affected differently due to forecasted demand, the accumulated effect on the total logistics cost is clearly non-linear, as can be seen in Figure 30. Another interesting remark to be noted is simply the trends of the various cost components involved in the network. The line-haul and last-mile delivery costs can be combined and be renamed as transportation cost, which can be used to illustrate the effect of transportation and inventory cost on the total logistics cost, as shown in Figure 30.

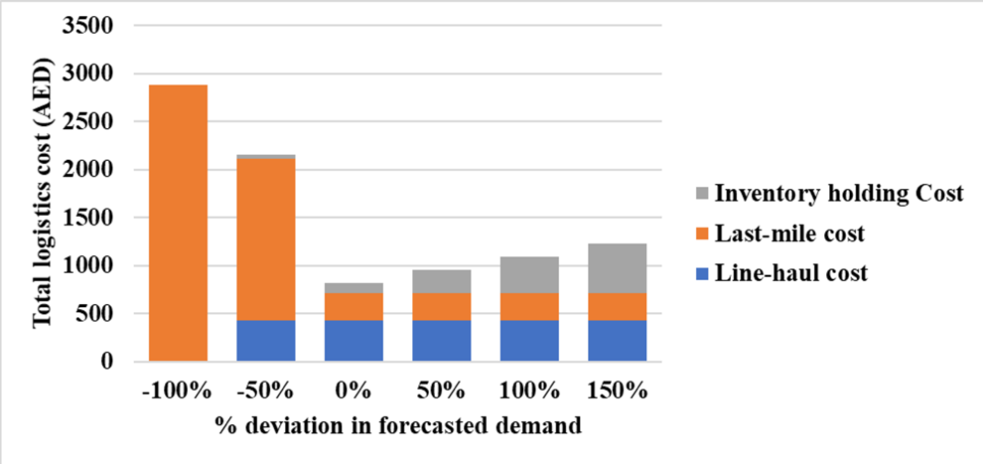


Figure 30: Sensitivity analysis: Error in forecasted demand

It can be seen that the total logistics cost is the minimum at a 0% deviation from the base case. When the forecasted demand is decreased from the base case, the transportation cost is dominant to the total logistics cost. However, on increasing the forecasted demand from the base case, the transportation cost becomes constant, and the total logistics cost is increased due to the increase in the inventory cost. Figure 31 shows the trade-off between the transportation and the inventory cost, and the graph obtained was very similar as described in Figure 6.

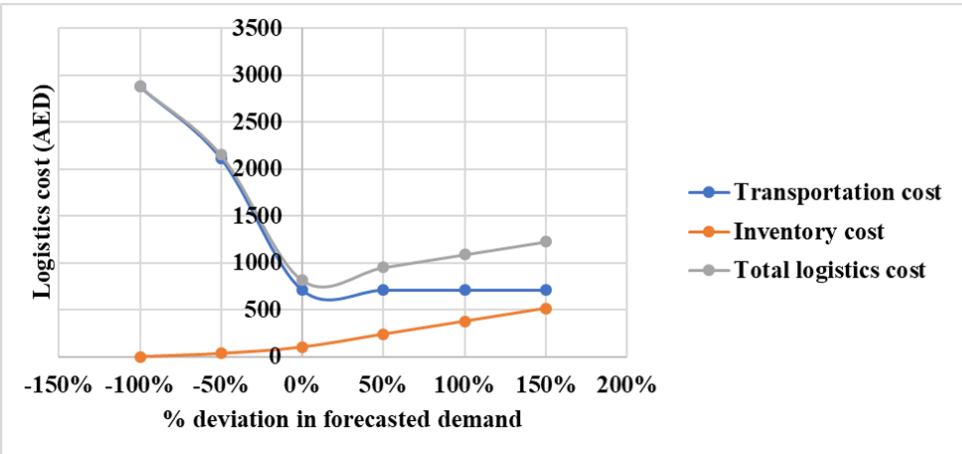


Figure 31: Effect of forecasted demand on the total logistics cost

5.1.4. Last-mile cost sensitivity. Since the last-mile cost depends on the last-mile cost/km and the vehicle capacity, each of these parameters are varied to observe the effect on the total logistics cost.

5.1.4.1. Last-mile cost per km. The effect of the last-mile cost per km on the total logistics cost was as expected. The parameter did not affect the line-haul and the inventory holding cost, however the last-mile cost increased linearly. Moreover, at -100% deviation, there was no contribution of the last-mile cost to the total logistics cost as expected. Table 22 summarizes the sensitivity results for this parameter.

Table 22: Sensitivity analysis: Last-mile cost per km

Deviation	Line-haul cost (AED)	Last-mile cost (AED)	Inventory holding Cost (AED)	Total logistics cost (AED)
-100%	426.6	0.00	102.6	529.2
-50%	426.6	108.00	102.6	637.20
0%	426.6	236.03	102.6	765.20
50%	426.6	324.00	102.6	853.20
100%	426.6	432.00	102.6	961.19
150%	426.6	539.99	102.6	1069.19

Figure 32 illustrates the linear change in the total logistics cost on deviating the last-mile cost per km.

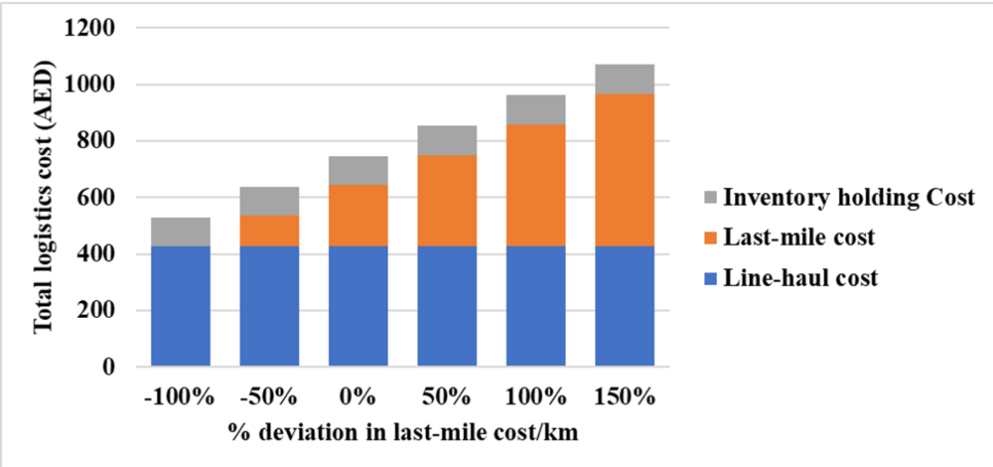


Figure 32: Sensitivity analysis: Last-mile cost per km

5.1.4.2. Vehicle capacity. In this analysis, the vehicle capacity was deviated from a range of -100% to 150% to observe the effect on the total logistics cost. Similar to the previous analysis, the line-haul and the inventory holding cost remained exhibited no change upon deviating the vehicle capacity. Moreover, a feasible solution cannot be achieved with a -100% deviation of vehicle capacity. The last-mile cost observed is the highest for the smallest feasible vehicle capacity, and the cost decreases upon increasing this sensitivity parameter. However, upon further increasing the vehicle capacity after a deviation of 0%, the total logistics cost remains constant. Table 23 summarizes the results for this analysis.

Table 23: Sensitivity analysis: Vehicle capacity

Deviation	Line-haul cost (AED)	Last-mile cost (AED)	Inventory holding Cost (AED)	Total logistics cost (AED)
-50%	426.6	402.91	102.6	932.11
0%	426.6	236.00	102.6	765.2
50%	426.6	216.10	102.6	745.3
100%	426.6	216.10	102.6	745.3
150%	426.6	216.10	102.6	745.3

Figure 33 demonstrates the relationship of the vehicle capacity to the components of the total logistics cost.

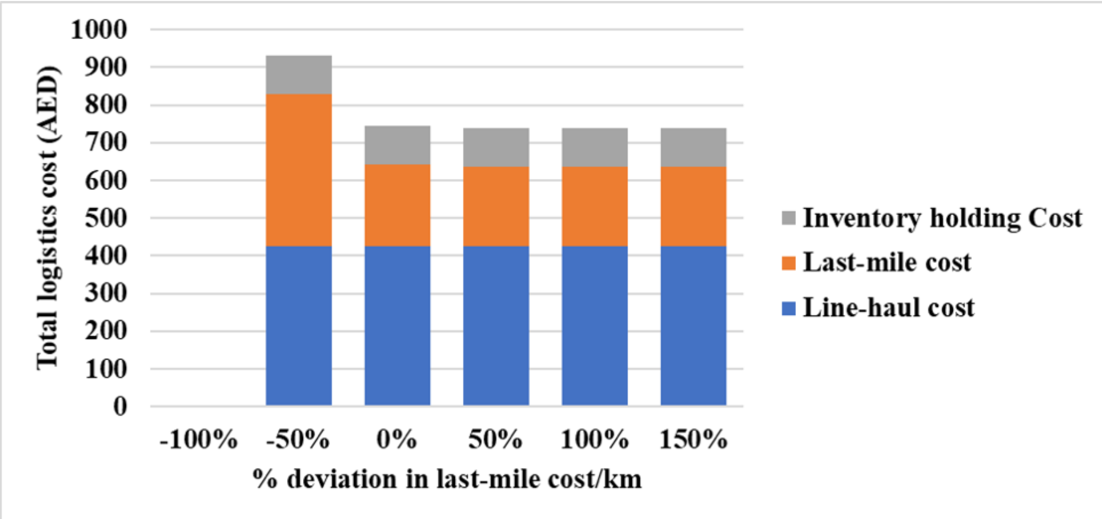


Figure 33: Sensitivity analysis: Vehicle capacity

5.1.5. Spider plot. A spider plot shows the effect on the output variable as a result of varying each uncertain input over its range, while keeping the other inputs at their base value. All the input parameters can be superimposed on the same graph, by showing the percentage changes from the base value of each variable across the x-axis.

As a result, the parametric lines for each input all cross at their mid-values, and the number of legs in the graph depend on the number of variables.

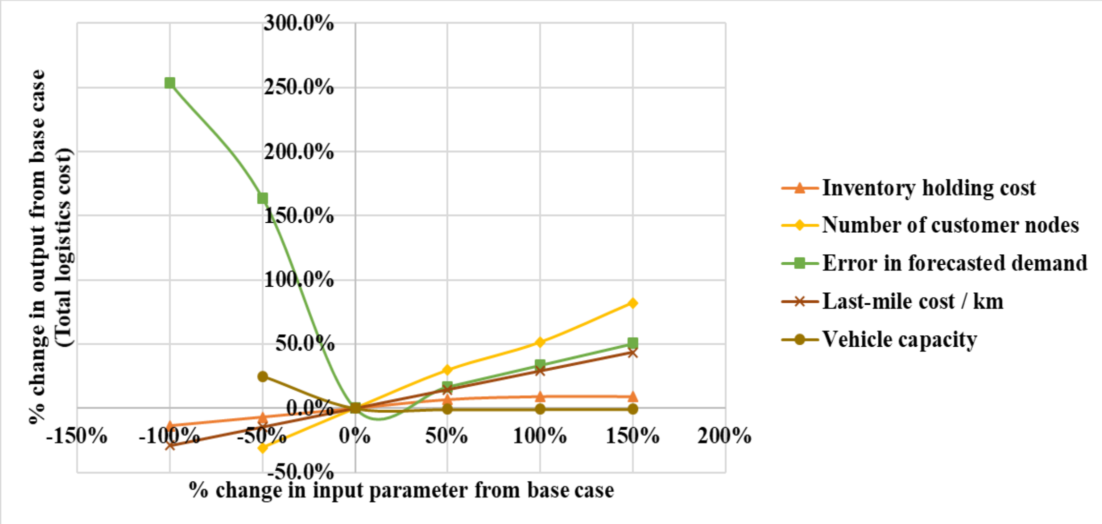


Figure 34: Sensitivity analysis: Spider plot

From Figure 34, it can be seen that the inventory holding cost, number of customer nodes and the last-mile cost per km have a positive correlation with the total logistics cost. On the other hand, the vehicle capacity has a negative correlation with the total logistics cost up to a deviation of 0%, and then the total logistics cost becomes constant. Moreover, all the parameters considered except for the forecasted demand, the slope of the trendline is almost linear, suggesting a linear change in total logistics cost with respect to the change in the input parameter.

The total logistics cost has an interesting trend upon the variation of forecasted demand. It can be seen that for a negative deviation of forecasted demand, the total logistics cost has a negative correlation with the forecasted demand. However, for a positive deviation of forecasted demand, the total logistics cost has a linear positive correlation with the forecasted demand. The most influential inputs are ranked as follows based on the slopes of their respective curves. For a positive deviation in the input parameter, the top three inputs are: (1) Number of customer nodes, (2) Forecasted demand, (3) Last-mile cost per km. On the other hand, if there is a negative deviation in the input parameter, the top three inputs are: (1) Forecasted demand, (2) Number of customer nodes, (3) Vehicle capacity.

5.2. Discussion of results

From our discussion this far, it can be concluded that inventory and distribution horizontal collaboration strategy can greatly optimize the network overall costs. However, it is to be noted that this proposed strategy is empowered through the concept of demand forecasting. Demand forecasting is essentially the combination of historical customer demand data with the predictions of future buying patterns to generate a forecast of the products required at a given place and time. Demand forecasting affects logistics greatly, and from our analysis, one can observe several insights on using forecasted demands in conjunction with horizontal collaboration.

Demand forecasting essentially gives us the information on how much product is required at a given place and time in advance. This can be translated on having the information on how much product needs to be shipped to the desired locations beforehand, empowering the network to preposition its assets to cut down costs significantly. This could clearly be observed by the operations involved in the models considering UCC level collaboration and the inventory and distribution horizontal collaboration, in which the products were prepositioned based on the forecasted demands of the products for the entire month. These networks enabled the use of available pallet space to preload strategic locations with the supply when required. This strategic move not only decreases the overall cost, but also enhances customer satisfaction by ensuring swift last-mile delivery of the product. Moreover, through the use of inventory collaboration, it is now possible to use the available inventory space in the off-seasons for fulfilling the products of other depots, hence increasing the asset utilization.

Demand forecasting greatly affected the freight transport costs as well. Logistics planning can be meaningfully optimized by decreasing unnecessary costs such as vehicle capacity under utilization and deadhead trips, which refers to the scenario when trucks are going to a target location without transporting any product. In our inventory and distribution collaboration model, the deadhead trips were significantly reduced by using the truckload (TL) line-haul strategy, as found in literature [31, 32]. Moreover, it can be seen that the vehicles in the network can be prepositioned, resulting in greater asset utilization and hence cutting overall logistics cost.

Another area in which forecasted demand planning affects the overall logistics cost is the inbound logistics. Knowing the demands in advance allows to trace back to determine accurate production runs, by which the planners can determine the raw materials required. Keeping the emergency safety stock into account, one can optimize the inventory by appropriately stocking the raw materials required for the production demand. However, this research was solely focused on outbound logistics, and hence this aspect is missing in our analysis and discussion of the model.

Chapter 6. Conclusion

With the growth in e-commerce and the increasing demands from consumers for ever-faster delivery options, it makes it almost impossible for the traditional logistics network to keep up. Therefore, the main goals for enterprises are maximizing added value and reducing total cost across the entire trading process by increasing speed and certainty of response to the market. Although third-party service providers play a huge role in the entire logistics process, the logistics network thereby created is still ‘static’ in the sense that it is limited to situations with consistent expected demands. Moreover, rapid technological advancements, such as Blockchain and the Internet of Things give rise to numerous innovative business practices in the logistics industry. The growing need for transparent, flexible, and easily adjustable logistics services introduces a relatively new concept called horizontal collaboration. Although a lot of research has been conducted on horizontal collaboration over the years, focusing on aspects such as the collaboration on the carriers’ transportation network operations, the authors could not find extensive research on inventory collaboration modeling.

In this thesis, a comparative study was conducted for three distribution strategies with different levels of inventory collaboration. The first strategy considered no collaboration among the suppliers in a network, indicating that each depot had to fulfill its own customers. In the second strategy, the suppliers consolidated their products to a third-party logistics provider for efficient distribution. The third strategy considered inventory and distribution collaboration within the warehouses in a logistics marketplace. The methodology is to compare the different strategies with respect to overall logistics cost of the network. For the scope of this thesis, the logistics cost comprised of the inventory holding cost, line-haul cost and the last-mile cost. After laying down a set of underlying assumptions, the Multi-Depot Vehicle Routing Problem (MDVRP) with supply and demand constraints was formulated for each strategy, and the mathematical models thus created were run on GAMS (as linear integer programs) to obtain the optimal solutions.

The models were tested using random datasets generated on varied levels of customer dispersion. It was determined that the model representing the strategy of full inventory and distribution collaboration resulted in the least cost in all cases with an average savings of 76.70%, followed by UCC level collaboration with average savings of 65.12%, as compared to the model with no collaboration. Therefore, it can be concluded that the location of the warehouses is one of the most crucial elements in the logistics cost, and inventory collaboration allows for a more distributed network with negligible fixed cost. Moreover, this analysis reinforces our intuition that the model depicting inventory collaboration within the depots will result in the least cost.

Although GAMS can provide exact solutions, it is known that the computational time increases exponentially with an increase in size of an NP-hard problem like the ones in consideration. Consequently, the use of GAMS was limited to small-sized problems for our models. That being said, an adaptation of the Variable Neighborhood Search (VNS) metaheuristic was developed to give a solution with good quality in a reasonable time duration. To be precise, we implemented a VNS that uses Variable Neighborhood Descent (VND) in the local search phase with three different neighborhood structures in the shaking phase. The proposed algorithm has been coded using C++ programming language, and the metaheuristic was run on the same datasets that were used in GAMS to validate the accuracy of the solutions obtained. It was found that the results obtained had a deviation of 2% - 8% from the optimal solutions, which is considered satisfactory. The algorithm was further analyzed by testing larger sets, and it returned solutions for 90 nodes within 3200 seconds.

At last, a sensitivity analysis was conducted to assess the effect of changing some key input parameters on the total logistics costs. The number of customer nodes, the inventory holding cost per unit volume, unit volume, last-mile delivery cost per km, vehicle capacity and the percentage error in forecasted demand were changed one at a time in a one-way sensitivity analysis study, and the effect of parameters' variation on the total delivery cost was observed. Overall, the most influential inputs are the number of customer nodes, error in forecasted demand, last-mile cost per km, and vehicle capacity.

One of the criticalities in horizontal collaboration involve key information and resource sharing, and therefore trust between cooperative firms is essential to collaboration. For future work, a crucial element would be to find partners for collaboration that are a ‘strategic fit’, as the main impediments to a cooperative approach are mutual mistrust and lack of transparency. We can also investigate various cost allocation methods, as the benefit belonging to cost savings are quite difficult to equally distribute among partners. Moreover, one area of interest will be to modify the existing model to consider the effect of total logistics cost on dynamic customer orders. Also, the model could be potentially enhanced by considering partial deliveries from the depots to the customers. Furthermore, we could relax some of the simplifying cost assumptions in order to take into account some of the costs we have not considered such as packaging and contract costs. Finally, the neighborhood structures used in the shaking phase and local search phase of the VNS algorithm can be improved in order to enhance the performance of the algorithm.

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Appendices

6.1. Appendix A: GAMS models

6.1.1. Model 1: No collaboration.

```
*Each customer node can only be visited once
ent(i2(j)).. sum((i,k), x(i,j,k)) =e= 1;
cap(k).. sum(i2(j), sum(p,dd(j,p))*sum(i, x(i,j,k))) =L= q(k);

*took depot into account!!
sec(arcs(i,j),k)$(i2(j)).. (u(i,k)   u(j,k) + n*x(i,j,k)) =L= n 1;

*flow contnuity
linknode(i,k).. (sum(j,x(i,j,k)) sum(j,x(j,i,k)))=e=0;

*each route can be served at most once. maximum one time a vehicle can leave the depot.
route1(k).. sum((i0(i),i2(j)), x(i,j,k)) =L= 1;

*supply capacity for depot
depotcap(i0(i),p).. sum(i2(j), dd(j,p)*z(i,j)) =L= supply(i,p);

*assign only if route from depot to customer
route2(i0(i),i2(j),k).. (sum(v, x(i,v,k))+sum(v,x(v,j,k)) z(i,j))=L=1;

add1(i0(i),i2(j)).. sum(k,x(i,j,k))=L=z(i,j);
add2(i2(j)).. sum(i0(i),z(i,j))=e=1;
add3(i2(j),k).. x(j,j,k)=e=0;

*objective function
objective.. obj=e=0.4338*sum((i,j),c(i,j)*sum(k,x(i,j,k)));

solve mtsp minimizing obj using mip;
```

6.1.2. Model 2: UCC collaboration.

```
ent(i2(j)).. sum((i,k), x(i,j,k)) =e= 1;

capacity(k).. sum(i2(j), sum(p,dd(j,p))*sum(i, x(i,j,k))) =L= Cap(k);

*took depot into account!!
sec(arcs(i,j),k)$(i2(j)).. (u(i,k)  u(j,k) + n*x(i,j,k)) =L= n 1;

*flow contnuity
linknode(i,k).. (sum(j,x(i,j,k)) sum(j,x(j,i,k)))=e=0;

*each route can be served at most once. maximum one time a vehicle can leave the depot.
route1(k).. sum((i0(i),i2(j)), x(i,j,k)) =L= 1;

*assign only if route from depot to customer
route2(i0(i),i2(j),k).. (sum(v, x(i,v,k))+sum(v,x(v,j,k)) z(i,j))=L=1;

add1(i0(i),i2(j)).. sum(k,x(i,j,k))=L=z(i,j);

add2(i2(j)).. sum(i0(i),z(i,j))=e=1;

add3(i2(j),k).. x(j,j,k)=e=0;

scollab(i0(i),p).. Supply(i,p)+ sum(d,LT(d,i,p)) sum(d,LT(i,d,p)) =e= SLT(i,p);

longhaul1(arcs(j,i))$(i0(i)).. sum(p,LT(j,i,p))=L=sum(p,Supply(j,p))*y(j,i);

longhaul2(arcs(i,j))$(i0(i)).. sum(p,LT(i,j,p))=L=sum(p,Supply(j,p))*y(i,j);

longhaul3(arcs(i,j))$(i0(i)).. y(i,j)=e=y(j,i);
```

```
*supply capacity for depot
depotcap(i0(i),p).. sum(i2(j), dd(j,p)*z(i,j)) =L= SLT(i,p);

*objective function
objective.. obj=e=0.4338*sum((i,j),c(i,j)*sum(k,x(i,j,k)))+0.482*(sum
    ((i0(i),d),tr(i,d)*y(i,d)))+ 2*sum((i,j,p),LT(i,j,p)) ;

model mtsp/all/;
solve mtsp minimizing obj using mip;
```

6.1.3. Model 3: Inventory and distribution collaboration.

```

ent(i2(j)).. sum((i,k), x(i,j,k)) =e= 1;

capacity(k).. sum(i2(j), sum(p,dd(j,p))*sum(i, x(i,j,k))) =L= Cap(k);

*took depot into account!!
sec(arcs(i,j),k)$(i2(j)).. (u(i,k)   u(j,k) + n*x(i,j,k)) =L= n 1;

*flow continuity
linknode(i,k).. (sum(j,x(i,j,k)) sum(j,x(j,i,k)))=e=0;

*each route can be served at most once. maximum one time a vehicle
    can leave the depot.
route1(k).. sum((i0(i),i2(j)), x(i,j,k)) =L= 1;

*assign only if route from depot to customer
route2(i0(i),i2(j),k).. (sum(v, x(i,v,k))+sum(v,x(v,j,k)) z(i,j))=L
    =1;

add1(i0(i),i2(j)).. sum(k,x(i,j,k))=L=z(i,j);

add2(i2(j)).. sum(i0(i),z(i,j))=e=1;
```

```
add3(i2(j),k).. x(j,j,k)=e=0;

scollab(i0(i),p).. Supply(i,p)+ sum(d,LT(d,i,p)) sum(d,LT(i,d,p)) =e=
    SLT(i,p);

longhaul1(arcs(j,i))$(i0(i)).. sum(p,LT(j,i,p))=L=sum(p,Supply(j,p))*
   y(j,i);

longhaul2(arcs(i,j))$(i0(i)).. sum(p,LT(i,j,p))=L=sum(p,Supply(j,p))*
   y(i,j);

longhaul3(arcs(i,j))$(i0(i)).. y(i,j)=e=y(j,i);

*supply capacity for depot
depotcap(i0(i),p).. sum(i2(j), dd(j,p)*z(i,j)) =L= SLT(i,p);

*objective function
objective.. obj=e=0.4338*sum((i,j),c(i,j)*sum(k,x(i,j,k)))+0.482*(sum
   ((i0(i),d),tr(i,d)*y(i,d)))+ 2*sum((i,j,p),LT(i,j,p)) ;

model mtsp/all/;
solve mtsp minimizing obj using mip;
```

Vita

Saif Mohammad Shahid was born in 1996, in Sharjah, United Arab Emirates. His primary and secondary education were attained from Delhi Private School in Sharjah, and graduated in 2013. He then pursued his major in Electrical Engineering with a double minor in Computer Engineering and Engineering Management, and graduated with Cum Laude honors from the American University of Sharjah, in 2018. Saif continued his education in the American University of Sharjah, and joined the Engineering Systems Management master's program while working as a full-time Graduate Teaching Assistant (GTA). His research interest is in operations research, logistics and supply chain.