MODEL THE VEHICLE ROUTING PROBLEM TO OPTIMIZE FREIGHT LOGISTICS MULTIPLE ECHELON NETWORK

U.D.D.M.Dahanayaka

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Udapola Dahanayakalage Dilshan Mahekha Dahanayaka

218053N

Thesis/Dissertation submitted in partial fulfillment of the requirements for the degree
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STATEMENT OF THE SUPERVISOR

The above candidate has carried out research for the Degree of Master of Science under my supervision.

Name of the supervisor: Dr. A.I.T.Gamage

Signature of the Supervisor: Date: 25th October 2022

Dr. A.I.T.Gamage
Senior Lecturer,
Dept. of Transport & Logistics Management,
Faculty of Engineering,
University of Moratuwa.

Abstract

The air freight supply chain is a crucial aspect of global trade. The freight forwarders act as the linking agents between the airside and the customers. The freight distribution strategies can be single-echelon distribution or multi-echelon distribution. Intermediate facilities like satellites are involved in the multi-echelon distribution and usually have several services which are utilized to reduce the transportation cost or travel distance and improve the level of service. Vehicle Routing Problem (VRP) is one of the most important combinatorial optimization problems and concerned with creating an optimal route to be used by a fleet of vehicles that served a set of customers. The literature study provides the basis for the study reviewing the development of the vehicle routing problem (VRP), its applicability in three-echelon distribution networks, solution methods, the importance of air freight distribution, and its application using VRP. Therefore, we developed a mathematical model for three echelon air freight distribution networks to minimize the total transportation cost. We discuss mixed integer linear programming formulations for this three-echelon capacitated vehicle routing problem with time windows (3E-CVRPTW) in the arc-based formulation. The connectivity between the three echelons has been made using demand as the connecting variable. Based on a case study at a freight forwarding company in Sri Lanka we developed hypothetical data set for the study with the support of expert knowledge. The 3E-CVRPTW problem was solved using a clustering-based heuristic approach and python programming language used to gain solutions. For ease of use, it was formed three zones using clustering analysis. It obtained the total transportation cost for the network and costs for each zone. Furthermore, it has calculated the delivery starting times for the 100 customers. Finally, the study has done a scenario analysis of varying vehicle fleet sizes, the number of customers served, and time windows of delivery. This research has opened a new path to develop the solution approaches for vehicle routing problems in a multi-echelon network associated with air freight distribution.

Keywords: Air freight, vehicle routing problem, logistics systems, freight transport, transport management

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LIST OF ABBREVIATION

Abbreviation	*Description*
VRP	Vehicle Routing Problem
CVRP	Capacitated Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
MDHFVRP	Multi-Depot Heterogeneous Fleet Vehicle Routing Problem
CMDVRPTW	Collaborative Multi-Depot Vehicle Routing Problems with Time Windows
MDVRP	Multi- Depot VRP
OVRP	Open VRP
TS	Tabu Search

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CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Aviation is an important element of the global economy providing over 60 million jobs and creating a vast number of economic activities. The air cargo industry is also gradually expanding while supporting to thrive off the market for goods like electronics, pharmaceuticals, flowers, industrial equipment, fruits, etc. According to Gardiner & Ison, (2007) in 2006, air freight was responsible for 36% of the global trade by value and since that, it has been growing by about 4.7% annually. Multinational large freight forwarders may operate their flights and the ground fleet to consolidate the accumulated freight from different clients. Land transport plays a major role in air freight delivery and the air cargo spends only 10%-20% in the air and the remainder of the journey happens on the ground. To benefit from the growth of trade value, air freight agents are under pressure to increase their capacities and enhance their processes.

It was conducted a comprehensive literature review suggested the scarcity of studies with a focus on air cargo distribution in city logistics. Air freight is a crucial link in global trade when considering speed and the timely delivery of freight (Debbage & Debbage, 2021). In the air freight supply chain, one of the bottlenecks that arise is with the freight forwarders when they connect the road transport and the air transport and during the consolidation and disassembling of freight. There is a large number of publications associated with the overall air freight supply chain, and the freight forwarders' internal process optimization or to assure efficiency are scarce.

In freight distribution strategy, the hierarchical level represents the path the cargo reaches to the last destination point. When freight arrives at the delivery location without modifying the mode of transportation it was traveling on, this method is known as direct shipping or single echelon. Between the source and the delivery point in multi-echelon distribution systems, there are intermediary points (warehouses, satellites, etc.) (Sitek & Stefanski, 2017). Guastaroba et al., (2016) presented comprehensive literature with an emphasis on freight transport planning with intermediate facilities. Intermediate facilities like satellites usually have the function of consolidation/ transshipments/ cross docks/value-adding services and which are used to minimize transportation costs or trip distance while improving service level (Archetti & Peirano, 2020). The use of satellites within the distribution network will create sustainable distribution with an effective logistics system.

In a multi-echelon network, one of the basic discussed problems is Vehicle Routing Problem. It is used to plan the best path for a fleet of vehicle or different modes of transport units to cater to customer demands given a set of various types of constraints (Sluijk et al., 2022). The VRP problem has many forms due to considerations like vehicle capacities, time limits, time windows, multi-depots, etc. The vehicle routing problem has many possible variations due to these and other features. Therefore, different variants of VRP can be identified, such as Capacitated VRP, VRP with time windows, two-echelon capacitated VRP, Dynamic VRP, etc. The VRP is the NP-hard type. A more advanced variation of CVRP is time windows VRP. Hard time windows and flexible time windows are the two types into which VRPTW can be categorized. We formulate an arc-based mathematical formulation using mixed integer linear programming for our study.

To streamline the process and make the most trips possible during the driver's shift, and minimize transportation costs satellite facilities are frequently used for vehicle replenishment. In this situation, two-echelon VRP is used, and normal trucks are used to transfer freight via satellite facilities, from the depot to the consumers (Grangier et al., 2016). Further, it was identified that few studies focus on three echelon networks that use VRP for optimization.

Furthermore, there are solution approaches that can be used for VRP. Exact methods, heuristic methods, and metaheuristics are such main approaches. In an exact method, to find the best solutions, the problem is formulated as a branching problem using a particular integer or mixed integer programming method. The methods can provide good solutions when the instances are too big for full convergence. In the heuristic approach, numerous stochastic problems do not have a particular answer that is proven to work under circumstances of reasonable scale. Heuristics are consequently necessary, and while they can't always be trusted to find the best answers to problems, they might be able to. Additionally, the most sophisticated metaheuristic algorithms use population search and local search techniques. In this study, we perform a clustering-based heuristic approach to resolve the three-echelon VRP with time windows. The clustering algorithm is an effective method for creating groupings of transportation routes in the network. The clustering algorithm's main goal is to organize demand nodes into clusters before figuring out vehicle routes for each group.

Hence this study aims to identify the process of optimizing the three-echelon air cargo distribution network while examining the effectiveness of the proposed method. The study addresses the research questions on how to optimize each echelon distinctly, using the VRP in the air cargo distribution network, how to formulate an optimized model for the vehicle routing problem in the three-echelon network, and also how to evaluate the proposed method's efficacy and applicability in a practical situation in air freight distribution.

1.2 Structure of the Thesis

The research dissertation’s chapters are organized as follows. The first chapter provides an introduction to the research and discusses the background of the study. Chapter two reviews the prior literature and theoretical concepts in the vehicle routing problem, its applications in the air freight industry, and the solution approach for VRP. Also, it outlines the research gaps, research questions, and research objectives after a thorough review of the literature. Chapter 3 presents the methodology of the study. This includes two parts as it presents the methodologies used to solve three echelon distribution networks and the solution approaches used in the case study. The results and the discussion are included in chapter four aligning the results with the objectives. It has presented the arc-based mathematical formulation for the VRP with time windows in three echelon distribution networks. All the assumptions and notations are included in general format. Then the case study analysis presents its data collection process, and solutions after solving the network using mentioned heuristic approach. Finally, it presents the experiment results on several scenarios we created. In chapter five we further present results, future research directions, and recommendations.

CHAPTER TWO: LITERATURE REVIEW

In here, we describe a review of the development of the VRP, its variants for distribution logistics and the application in intermediate facilities, the special variant of VRP with time windows, and the applications of VRP in three echelon networks. Furthermore, we review the solution approaches that have been discussed for VRP such as exact methods, heuristic approaches, and metaheuristic approaches. Finally, it discusses VRP applications related to the air freight transport industry. And it has followed with history, growth, connectivity with supply chains, the role of road feeder services and freight forwarders, associated security and risks, innovations, and trends in the air freight industry. And finally, research objectives and questions have been presented.

1.3 Development of VRP

Dantzig & Ramseur, (1959), introduced the classical vehicle routing problem approximately sixty years ago. This first introduction of VRP was about a real-world application of gasoline delivery to service stations. In 1964 Clarke & Wright, (1964) proposed an improvement for Dantzig & Ramseur, (1959) approach, which was an effective greedy heuristic. Mentioned two studies paved the base for many models and algorithms that were proposed as the solutions of numerous versions of VRP.

Present VRP types are far diverse from the introduced models by Dantzig & Ramseur, (1959) and Clarke and Wright (1964). The recent VRP applications discuss real-life complexities like time-dependent travel times, time windows for pickup and delivery, capacity limitations, multiple depots, heterogeneous vehicle fleets, etc.

1.3.1 Definition of Vehicle Routing Problem

Vehicle Routing Problem is one of the most important combinatorial optimization problems and is involved with creating the best possible route to be used by a fleet of vehicles that served a group of customers. VRP is a developed extension of the travel salesman problem.

Several factors influenced the VRP problem to create various variants such as vehicle capacities, time constraints, time windows, multi-depots, etc. These and the other characteristics helped to create numerous modifications of the VRP. Further, the problem is created with different constraints and variables according to the dynamic characteristics. This is a challenge that makes a complex problem where various criteria and limitations have to be considered at the same time as the requirements of the clients.

The distribution cost contributes significantly to a product's final retail price and helps to cover both fixed and variable costs. The high product demand can be achieved when the companies find ways to reduce the above costs. The fixed cost incurs from the driver's wage or the vehicle usage cost which affects to distribution company only using the vehicle irrespective number of customer orders served and the route they chose. However, variable expenses result from the price of gasoline or the length of the route. In real-life problems the restriction, parameters are included and related to different VRP variants. Therefore, it requires defining the VRP variants according to real-life problems, the problem formulation, and the objective function in order to match the total cost. All these factors are important to investigate the most suitable optimization technique that may cost-effectively focus on the problem.

In earlier stages, most transportation companies faced difficulties in finding the process of vehicle routing or scheduling to execute because of the use of maps and experts' empirical understanding. Today with the use of computers and routing and scheduling software the process has become easier though changes are continuously arising with the large volume of data and increase of demands and requirements. It is clear that today logistics companies require extremely advanced systems that are effective for delivery routing and execution. Companies in this situation must properly understand the numerous variations and parameters that affect both the algorithms and daily operations.

1.3.2 VRP Variants for Distribution Logistics

We explain the variations concerning the routing of vehicles and scheduling and their applicability to actual-life scenarios. In real-life distribution cases, the capacities constituted in vehicles are considered a main factor of the VRP(Kim et al., 2015). And it is the very first variant considered by researchers and practitioners. It can be found two variants of the VRP related to capacity. Firstly, it can be described that all vehicles are equal, and they have similar capacity, so then call them capacitated VRP (CVRP), secondly, multiple types of vehicles are used with different capacities, fixed and variable costs, and different fleet sizes. In real scenarios, companies maintain a fleet of identical vehicles. In cost-effective practices, companies utilize various kinds of vehicles. Small-size vehicles are used to serve last-mile distribution while large vehicles are used to serve larger volume orders and between customers and retailers who are located in more substantial spaces. In more general practice is that it is expected the vehicles are returning to the central depot following the completion of their paths.

Third-party logistics companies commonly deal with transportation companies to get a fleet of vehicles for distribution as a fact to reduce their fixed cost. In such a situation, the partner's vehicles do not essentially require returning to the depot following completing the route and this is accepted as the Open VRP (OVRP) by Zachariadis & Kiranoudis, (2010). The researchers have considered two or three-dimensional loading constraints to ensure that distributed freight can be loaded onto vehicles feasibly without considering the fleet type as homogenous or heterogenous (Zachariadis et al., 2016). Researchers have split the problem into two main problems as packing and routing. Furthermore, Truck and Trailer VRP (TTVRP) can be seen as a different variation that is associated with the loading capacity. In some scenarios, customers will be served by a truck-pulling trailer, even though many were served by a specific truck(S. W. Lin et al., 2010). So these are primarily related to the supplies and collections in metropolitan regions and countryside regions with limitations to ease of access (Luiz Usberti et al., 2013).

There are many occasions when companies have to use lower-capacitated vehicles when the limitations like traffic jams, limitations for ease of access, and environmental laws in cities have occurred (Quak & de Koster, 2008; Razmi Rad et al., 2021). In these situations, the vehicles can simply serve a limited number of customers within a journey, but they are capable of completing several journeys in an operating day which leads to Multi-Trip VRP (MTVRP)(BrandãO & Mercer, 2017).

Further, replenishment purposes of vehicles are achieved by satellite facilities to optimize the process and to proceed with the highest number of trips in the driver's shift. Two-Echelon VRP is used in this context and the distribution of freight from the depot to consumers is handled by routine vehicles via satellite services (Grangier et al., 2016). In Two Echelon VRP, there are two routing protocols: A vehicle leaving from the depot, supplying to satellites, and returning there; the other is for vehicles leaving from satellites, traveling to consumers, and returning to satellites (Crainic et al., 2010). The multi-Echelon VRP variant is considered when there are more than two layers of distribution.

The setting of parameters for VRP has been determined by the requirements of the customers. One of the common types of variants is the VRP with Time Windows (VRPTW). In such a situation, the customers specify a window of time during which the order should be delivered. The hard time windows are defined as when the vehicle must wait till the time window is opened if it arrives before the beginning of the period, and also it cannot reach later than the end of the period as well (Brandão de Oliveira & Vasconcelos, 2010). Soft time windows mean when the vehicle arrives once the window of time has expired, but at an extra fee. This variation is important because most of the end customers decide on a time window to get delivered their goods, and it is connected to high customer satisfaction and the accuracy of deliveries.

Good interpersonal relationships between the parties can enhance the condition of services offered. Previous era a novel modification of the VRP has developed, which is the consistent VRP (ConVRP). It has built upon prioritizing the trust between customers and companies. Therefore, companies have decided to reduce the number of drivers that each client has to deal and they construct consistent routes over some time (Feillet et al., 2014).

It is important to emphasize that logistics operations do not stop at the time of the transport of commodities to customers, but there are situations when customers are returning the products. It studied the issue of supplies and pickups during the implementation of routes in VRP with simultaneous pickups and deliveries (VRPSPD). The VRPSPD defines when the goods delivery starts from the main depot and deliver to the buyers, as pickups are filled to the vehicles before sending to the depot (Montané & Galvão, 2006). As the entire capacity of vehicles cannot be exceeded, delivery and pickup loads are taken into account at every stage. VRPB has another limitation which is that each route's pickup goods are collected following delivery, and also it simplifies the problem (Goetschalckx & Jacobs-Blecha, 1989). The two variants VRPB and VRPSPD both are counted in the term VRPPD (VRP with pickups and deliveries) because they are both involved in pickups and deliveries.

Environmental pollution has been a major concern in research in terms of efforts to reduce noise, traffic, and CO_2 emission, to raise citizens' standards of living. The major part of CO_2 emission is accountable by road freight transportation which cannot be ignored by the transportation companies. Green VRP(GVRP) is identified by the literature as a problem to minimize CO_2 emissions(C. Lin et al., 2014). The Pollution Routing Problem is another VRP similar to GVRP which is more difficult to solve because it depends on the vehicle's speed and also the vehicle's weight at each stage of distribution. This specific variant was firstly studied by Bektaş & Laporte, (2011). The reduction of pollutants and CO2 emissions is also made possible by hybrid and electric vehicles, which can run on both regular gasoline and electricity. The problems in this context are recognized as Electric VRP (EVRP) and Hybrid VRP (HVRP) and it attracts the company's attention for research (Mancini, 2017). Therefore, the four VRP variants, (HVRP, PRP, EVRP, and GVRP) are counted under the same classification GVRP according to the literature classification.

The amount of time required to travel among delivery points, pickup positions, and depots has a significant impact on how accurate deliveries are. The problem is tackled with the purpose of a task where it uses the leaving time as the independent variable and the problem is Time-Dependent VRP (TDVRP) (Andres Figliozzi, 2012). The parameter is significant for the estimation of the feasibility of routes, both the amount of traffic and the distance between nodes. When delivery and pickup orders are known before the start of routes, the version provides initial routing and scheduling. During the execution of roads, there can be unexpected events(Zeimpekis, 2007). In such a context, the changes in delivery schedules are used to satisfy new orders from customers and mitigate delays.

The dynamic and stochastic versions of the problem should be used with the applicability to face each problem effectively, and it can be supported by the communication between the parties of transportation companies(Pillac et al., 2013). Most commonly the requirement for dynamic routing occurs due to traffic jams that can affect the stochastic scheduling methods(G. Yu & Yang, 2017).

Another noteworthy variation that is based on the number of distribution facilities supporting the dispersal of freight is the multi-depot VRP (MDVRP). Mostly when a company handles several distribution centers, the nearest warehouse to the customer's order gets to deliver to the customer. In that context, MDVRP can be considered in a more simplified version such as a sequence of multiple single-depot problems. This will make the problem-solving process much easier with everyday new orders, that create non-fixed routes. In a network of cooperative distribution that cooperates, a group of companies, cannot be solved the problem easier in order to optimize the operation. The Collaborative VRP is an expansion of MDVRP that may increase the efficiency of the operation of the logistics network, increase vehicle load factors, and decrease unnecessary transits(Wang et al., 2017). Hence, the multi-depot VRP and collaborative VRP can be classified under one name MDVRP.

The Split Delivery VRP(SDVRP) and Periodic VRP(PVRP) are two variants that are less commonly used by transportation companies. The SDVRP relaxes the requirement that each client stays at just one time and by a single vehicle, allowing the clients' demand to be distributed among the available vehicles(Silva et al., 2015). According to Archetti et al., (2008) certain relaxation may be beneficial for several delivery situations where the average client demand is slightly more than the capacity of the vehicle, but offers an increased load factor of vehicles with fewer delivery routes. As it has described by Coene et al., (2017) the PVRP uses a planning horizon in days or weeks to construct routes. This model is useful for logistics companies with the need for an optimal plan for a certain period of fixed orders.

Most cases consist of multiple constraints, complex parameters, and challenging features that reflect real-life routing problems. According to Rabbouch et al., (2021)and Caceres-Cruz et al., (2014)the real-life constraints are heterogeneous fleets of vehicles, time windows of customers, the capacity of vehicles, different warehouses, etc. The mentioned constraints are related to some of the VRP variants that have been discussed before such as Multi Depot, Pickup and Deliveries, Heterogeneous fleet, and time windows. Furthermore, (Penna et al., 2018) have managed to solve all the above-mentioned VRP variations at the equivalent time. The Rich VRP is introduced in last years as the variant which considers multiple constraints at the same time (Lahyani et al., 2015). It uses algorithms dealing with variants to simplify the problem.

An inventory routing problem (IRP) is another extension of VRP and it discusses the problems related to intermediate facilities. Peres et al., (2017) evaluated a multiproduct IPR with scheduled transshipment where several distribution centers and factories are included in the network. The method they suggested was an accurate formulation and building of a Hybrid Randomized Variable Neighborhood Descent (HRVND) for large-scale cases. It was proven that the number of required vehicles is reduced with the cooperation of distribution centers. The overall cost and risk-based transportation have been reduced by Arab et al., (2018) in their multi-period IRP distribution study. The methods used were nondominated classifying GA and a multi-purpose imperialist competitive algorithm. The single product IRP with transshipment was discussed by Lefever et al., (2018)where branch and cut formulation and suggested four techniques have been used for performance increment. Similarly, the Branch and Cut method was utilized by Qiu et al., (2019)focusing on the management of inventory in intermediate facilities. They suggested a mixed integer linear programming model create the model. Three phase metaheuristic algorithm was proposed by Bertazzi et al., (2019)considering a new variation of IRP. A multi-depot IRP was considered by Zakharov & Shirokikh, (2018) which serves a certain group of customers in each depot. The Direct Coalition Induction algorithm was utilized to examine characteristic functions. The demand uncertainty within the intermediate facilities was minimized with the use of two approaches, a safety stock deterministic model and sample median approximation in the study conducted byYadollahi et al., (2019).

The discussed variants of the VRP are the most commonly addressed variants by logistics companies when facing challenges in operations. The complexity of numerous variables, and different constraints force logistics firms to make the best-optimized routes and minimize costs.

1.3.3 VRP with Time Windows

Time windows VRP is an extended version of CVRP. Hard time windows and flexible time windows are the two types into which VRPTW can be divided. (Toth et al., n.d.-a). Vehicle routing problem with hard time windows has been solved using various approaches such as neighborhood-based heuristic(Imran et al., 2009), improved ant colony optimization(B. Yu & Yang, 2011), bee colony-inspired approach(Häckel & Dippold, 2009), hybrid ant colony optimization (el Hassani et al., 2008), etc. It studied a scheduling problem according to time and invocation status for a 40-vehicle company by Knight & Hofer, (1968). Algorithms for vehicle routing and scheduling issues with time window limitations were created and studied by Solomon (1987). It was constructed a local search algorithm for TWVRP by Savelsbergh, (1985). (Taniguchi & Shimamoto, 2004) created a dynamic vehicle routing and scheduling model using actual travel times, and times were updated via dynamic traffic simulation. Desrochers et al., (1992) developed a new optimization algorithm for VRPTW solution based on column generation. Furthermore, considering perishable food delivery, Hsu et al., (2007) developed a probabilistic VRPTW focusing on time-dependent and time-varying temperatures within a day. Tang et al., (2009) proposed a vehicle routing problem with fuzzy time windows and functions used to characterize the service offer concerns related to time window violation.

The heuristic approach is another approach to obtaining solutions. Kritikos & Ioannou, (2010) solved the vehicle routing problem with time windows utilizing a heuristic approach that addressed balancing cargo carried by vehicles. Furthermore, Qureshi et al., (2010) developed a model with soft time windows for VRP and a heuristic-based genetic algorithm used for obtaining the solution. A study was conducted for heterogeneous VRP with time windows using a semi-heuristic tabu search algorithm by Repoussis & Tarantilis, (2010). Flexible time windows were included in a multi-objective VRP which was resolved using a hybrid ant colony optimization algorithm(H. Zhang et al., 2019).

MDVRP, or multi-depot VRP, is another well-known variation of VRPs. Therefore, multi-depot VRP and location routing problems were assessed by Laporte et al., 1988) Tabu search heuristics algorithm was used for the study by Renaud & Boctor, (2002) and (Ho et al., 2008) conducted an MDVRP using a hybrid genetic algorithm. A study used a heuristics approach aligning with adaptive memory and tabu search algorithms where vehicles used intermediate storage points(Crevier et al., 2007).

multi-depot heterogeneous fleet VRP (MDHFVRP) is a difficult variant of the VRP. In this situation, MDHVRPTW, (Xu et al., 2012) created a variable neighborhood search algorithm to resolve the problem. Similarly, (Salhi et al., 2014) devised a formulation-based algorithm centered on a variable neighborhood search for the MDHVRPTW problem. With the purpose of routing delivery and setting up tools Bae & Moon, (2016), created a mixed integer programming model and used a heuristic method based on nearest neighbor and genetic algorithms for obtaining a solution. Furthermore, (Bezerra et al., 2018) used a general neighborhood search metaheuristic algorithm. Research performed by J. Li et al., (2018) compared the fuel consumption of two models of MDVRP wherever sources are divided and resources are not divided scenarios. Additionally, Wang et al., (2020) examined collaborative multi-depot VRP with time windows- (CMDVRPTW) which applied created the solution using a hybrid heuristic algorithm.

1.3.4 VRP with Three Echelons

A study conducted by Hashemi et al., (2022) aims to minimize delivery times and systems costs for retailers in the three-echelon supply chain which included manufacturers, distributors, warehouses, and retailers. Two modified MOPSO andNSGA-11algorithms are built and solved the model. Since it is a multi-objective model in three echelon supply chain it supports filling the gap between routing and location choices.

Elalouf et al., (2021) considered a three-echelon blood sample supply chain that includes clinics, centrifugation centers, and testing labs. They presented a novel simulation-based approach to VRP which would be a decision support tool for resource utilization and to improve service quality. Beheshtinia et al., (2021) aim to reduce the overall cost of manufacture, transport, and stock keeping in three echelon pharmaceutical production supply chain in Iran that consists of a two-layer transportation system. The uncertain nature of the model parameters made to create one possibilistic model and one robust possibilistic model. A study focused on redesigning an actual distribution network distributing two commodities of an electronic company using a multi-echelon capacitated location routing problem(Sanghatawatana et al., 2019). They used the clustering technique to gain the solution. Initially, the problem was segregated into two stages a facility location-allocation problem and a multi-depot VRP. Another Np-hard problem is the Location Inventory routing problem. Saragih et al., (2019) studied a three-echelon supply chain that makes inventory decisions in all three echelons and built a location inventory routing problem. A heuristic method was developed for the problem and simulated annealing was utilized to enhance the result.

Sustainability measures in the supply chain are one of the recently emerging trending topics. Giallanza & Puma, (2020) designed a three-echelon fuzzy green vehicle routing problem considering a situation analysis of a Sicilian agri-food supply chain. The problem was solved using non dominated sorting genetic algorithm. Similarly, a sustainable three-echelon distribution network was evaluated by Validi et al., (2021)with the use of three meta-heuristic optimizer solution methods, and the model was validated from a case study of an Irish dairy processing logistics network. It aimed to minimize total costs and total Co2 emissions in transportation.

Demand uncertainty issues such as the bullwhip effect create some undecided and critical issues in the supply chain and logistics. Therefore, Nikfarjam & Moosavi, (2021) proposed a two-stage approach for a three-echelon single-item supply chain to examine the inventory routing problem. Large-scale instances were solved with the use of a new accelerated Benders decomposition algorithm and results were contrasted with the performances of the Genetic algorithm and mathematical programming. Furthermore, Huang et al., (2018) conducted a study and build up a model on three echelon location routing problems with a directed graph. This is solved using a quantum-inspired evolutionary algorithm and genetic algorithm. In an efficient logistics strategy, the cross-docking process is an important aspect. Ahmadizar et al., (2015) suggested a three-echelon supply chain, a model of two-level vehicle routing with cross docking. The aim is to optimize schedules and routes of vehicles and consolidate products to minimize costs. Mousavi et al., (2013) introduced a novel combined model for cross-docking systems designed under a fuzzy nature. The model built up a new vehicle routing and scheduling model with several cross docks. Furthermore, inventory and transportation costs can be considered the main contributors to expenses in logistics. Fu, (2013) aimed to find out the combined routing and inventory policy to reduce a long-horizon system cost in a three-echelon distribution system. It developed efficient algorithms for three-echelon VRP by decomposing the original problem into a two-echelon subproblem. Additionally, vehicle routing and location routing are commonly used by companies to strengthen their competitive advantages. Therefore, Chang et al., (2010) develop a three-echelon logistic model considering vehicle routing, consumer behavior, and competition to determine convenient transshipment routes and optimal locations for the stores.

1.4 Solution Methods of VRP

There are several approaches to solving a VRP and we review some special approaches related to capacitated VRP. It discusses the exact methods, heuristic methods, and metaheuristic methods.

1.4.1 Exact Methods

The problem is viewed as a special integer or mixed integer programming method and employed as a branching formulation in a way to obtain optimal solutions. When the number of instances is too great for full convergence, the approaches can produce good results.

1.4.1.1 Method -Integer L-shaped

This method is a branch and cut algorithm which will be able to start using an earlier retrieved possible result or with no feasible solution (Jabali et al., 2014). A former study used the L-shaped method as the solution approach for single-vehicle CVRP (Laporte et al., 2002). For all probability distributions, it is presented in a general way to find L in the problem. It used an L-shaped method to get results to VRP with time windows and stochastic demand M. S. Chang, (2011). According to Laporte et al., (2002b) the exact separation method produces better solutions compared to the heuristic used in the study. Gendreau & Rei, (2007) introduced local branching for 0-1 integer L-shaped method to resolve single vehicle CVRP.

1.4.1.2 Method - Branch and Cut

This method is suggested for handling two variants of the problem when the sample space's cardinality is not very huge.Kenyon & Morton, (2003) proposed a branch and cut method to resolve the VRP with stochastic time windows. They suggest the branch and cut method in a Monte Carlo sampling when there is substantial sample space. Generally, the technique does not provide an optimal solution. With a confidence level, the distance between the optimal value and the objective function of the resolution can be bound. Similarly, Adulyasak & Jaillet, (2015) used this method to explain the robust CVRP with the travel time of ambiguity constraints. Another primary variation is the method used to add the cuts; whereas in Kenyon & Morton, (2003) constraints are further straightforward, Adulyasak & Jaillet, (2015) cuts are applied repeatedly while a workable vector is discovered. Similarly, Gounaris et al., (2013) used the same method to solve a Rich VRP using CPLEX 12.1. Furthermore, Beraldi et al., (2015) found solutions for mixed capacitated general routing problems using branch and cut algorithm. It was presented that the B&C algorithm was capable to give the best possible results within a limited computational time for 3 out of 23 instances.

1.4.1.3 Method - Branch and Price

A new technique in the Branch and Price approach, the Dantzig-Wolfe method was used in a study on CVRP with Stochastic demand by Christiansen & Lysgaard, (2007). Even if an integer solution to the problem cannot be found, the consumer order for each path is recognized. As a result, it is possible to calculate the estimated failure cost before knowing the integer solution. X. Zhang et al., (2021) used an exact B & C algorithm and an approximation counterpart as the method to solve a capacitated vehicle routing problem. The method was capable to enhance the result of the existing occurrences. The study by Bulhões et al., (2018) goal of the Minimum Latency Problem (MLP), a variation of the famous Traveling Salesman Problem, is to reduce the total number of client waiting periods. Errico et al., (2016) employed branch-cut-and-price algorithms to resolve the set partitioning issue known as the VRP with hard time frames and stochastic service timings.

1.4.2 Heuristic Approaches

Numerous stochastic issues lack a specific solution that is known to be effective for situations of acceptable scale. Heuristics are therefore required, and while they cannot be relied upon to always identify the best solutions to issues, they may be able to do so.

1.4.2.1 ALNS Method- Adaptive Large Neighborhood Search

initializing from a primary solution created using an procedure termed stochastic path scanning, which is an adapted form of the path scanning (PS) approach, the capacitated arc routing issue with stochastic needs was solved by (Laporte et al., 2009). Lei et al., (2011) used ALNS heuristics to resolve CVRP with time windows, and the initial solution was retrieved using a push-forward insertion heuristic. Furthermore, Chen et al., (2014) proposed an adaptive large neighborhood search algorithm to solve CVRP with travel times. Here, the algorithm discontinues the identification of no enhancement after a concerning number of repetitions.

1.4.2.2 Dynamic Programming

Dynamic programming techniques, as opposed to stochastic programming, are often used to identify a policy as opposed to a temporary fix. In the early stage, Yang et al., (2000) used a dynamic programming algorithm to gain solutions for stochastic CVRP. It aimed to discover the ideal refilling policy. A study conducted by Secomandi & Margot, (2008) used dynamic programming to solve the single-vehicle CVRP with stochastic demand with a formulation using the Markov decision process. A cyclic heuristic is used to solve the VRPSD with the development of a two-step rollout algorithm. Additionally, Zhu et al., (2014) used a bilevel Markov decision process for a two-vehicle CVRSD problem and modeled the coordination between vehicles in the paired cooperative re-optimization. Soysal & Çimen, (2017) addresses a green time-dependent CVRP and used simulation-based restricted dynamic programming heuristic and simulation as one of the solutions approaches. It gives promising results within a short computation time compared to the classical approach. Gromicho et al., (2012) introduced a restricted dynamic programming algorithm which is a construction heuristic that many restrictions and objective functions guide to an optimal algorithm.

1.4.2.3 Local Search

A common local search method is the Tabu search (TS) heuristic. A study conducted on CVRP with stochastic demand by Haugland et al., (2007) used the tabu search heuristic to design delivery districts. The districts are planned with a long-term, fixed viewpoint so they can be used for a variety of demand realizations. Zeng, (2019) used improved particle swarm optimization based on tabu search to mitigate issues that arise in applying particle swarm optimization to solve VRP. It has studied the aspects of TS such as the local search for combinatorial optimization problems as a strategy for urban good distribution(Meliani et al., 2019). To solve the challenge, Xia et al., (2018) focus on building a double-objective mathematical programming model for distance-constrained and capacitated VRP with split deliveries by order and developing an effective adaptive tabu search algorithm (ATSA). A study used the tabu search method to work out a CVRP with soft time windows and service costs (Taş et al., 2013). The initial solution was modified utilizing tabu search heuristics. A study was conducted by Ahmadi-Javid & Seddighi, (2013) to solve a location routing problem with disorder risk and resolved using a two-step heuristic. Additionally, a VRP with stochastic service time was proposed to solve using generalized variable neighborhood search (GVNS) for a study conducted by (Lei et al., 2011a). The initial solution was obtained using a Clarke – Wright algorithm and a local search is done by a variable neighborhood descent scheme.

1.4.3 Metaheuristic Algorithms

The more sophisticated metaheuristic algorithms use approaches for local and population searches. Population-based heuristics focuses on creating a fresh answer from a collection of results in a way by creating them cooperate from a learning process or combining and pairing existing ones. Population-based heuristics can be identified as Genetic Algorithms, Memetic Algorithms, Particle Swarm Optimization, Evolutionary Algorithms, Ant Colony Optimization, and Scatter Search. Local search heuristics are commonly categorized as Tabu Search, Simulated Annealing, Variable Neighborhood Search, Iterated Local Search, Large Neighborhood Search, Greedy Randomized Adaptive Search Procedure, etc.

The most common metaheuristic algorithms are Genetic algorithms (GA’s). They are created because of the inspiration from biological evolutions. The generation of GA is firstly formed when a population(parents) of solutions is selected. According to the fitness functions of the parents two parents are selected in each iteration. Then these two are combined via the crossover procedure to gain offspring(children). To ensure the diversity of the population the mutation procedure is applied. The finest results are chosen to use as parents in the following iterations. There is an improved edition of

GA's called Memetic algorithms which apply a local improvement method for each child. Genetic algorithms and Memetic algorithms both belong to the large category of Evolutionary Algorithms (EAs)Labadie, (2015). In Scatter Search Method, it requires a small set of solutions, that contains both diversified and a good set that can apply local improvement methods. The swarm-based algorithms are another general method that includes Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). According to the probabilistic rule, the paths are built when ants move in the graph in the ACO method. But in PSO, there exist a population of particles that each one goes from its place to a different place in the exploration area. The best position a particle achieved and the best solution they get to influence the movement of each particle.

According to Konstantakopoulos et al., (2021)Local Search metaheuristics focus on simply relocating the current solution to a different location inside the local area. Another most frequently applied algorithm is Tabu Search which relies on the search-continuation principle. A change is used in the present answer even if the goal declines. Another common algorithm is Large Neighborhood search (LNS) which investigates a wide exploration area and its primary result is partially damaged because elimination operators and reinsertion operators will repair at the final stage. The Adaptive LNS method is also an extension of LNS which applies the efficient operator that is subject to vary over the search in each iteration.

Another method is the Guided Local Search (GLS) method which functions in a wider search space and avoids local optimum with the support of assignment of penalties to the objective function. Furthermore, some other metaheuristics support avoiding confining in local optimum such as Simulated Annealing, Variable Neighborhood Search, and Iterated Local Search. Most commonly the algorithms get combined to optimally solve the VRPs. The hybrid algorithms were developed in past years while combining meta-heuristics methods (Kaboudani et al., (2020).

1.5 Air Transport and Its Importance

Aviation is an important part of the global economy providing over 60 million jobs and creating a vast number of economic activities(Khan et al., 2020). Aircraft manufacturers are endlessly trying to construct better and bigger aircraft to satisfy the growing needs of the stakeholders. Furthermore, the air cargo industry is also gradually expanding while supporting to thrive the market for goods like electronics, pharmaceuticals, flowers, industrial equipment, fruits, etc. According to statistics, 35% of the value of all freight transportation worldwide is categorized as air cargo (Bombelli et al., 2020).

1.5.1 Air Cargo History

Commercial aviation began around 1910 with the recognition of the possibility of developing aircraft for practical applications like mail transportation to the US Post Office Department(Cohen et al., 2021). In 1926, the newly established Lufthansa company air lifted 1000 tons of air cargo along with 6000 passengers. World War 11 witnessed significant improvements in aviation technology with advancements in military aircraft and heavy cargo transportation. In the beginning, the freight on international long-distance routes was maintained at a moderate level and constitutes mainly airmail which require limited capacity. KLM, Deutsche Lufthansa, and Air France became the pioneers in carrying newspapers, gold bullion, spare parts, etc. and KLM was the first to transport large animals like horses(Sales, 2016). Earlier, most freighter aircraft were either converted commuter aircraft with removed seats or ex-military aircraft. The Berlin Airlift was an important milestone in air freight progress. During the second World War Berlin got the supply of essentials for over 2 million citizens through air transport. Further, they developed a new large airfield that required flying equipment and materials for building it. This Berlin airlift was the initiation of air freight to deploy with its maximum efforts (Sales, 2016). And it gave significant breaking points and lessons to learn from the incident which paved a giant step into the next level of profitable air freight operations.

1.5.2 The Growth of Air Freight

The industry provides different appropriate aircraft varieties to cater to the needs of customers with different ranges of products and product sizes. Mainly in the county or local markets, international mail, newspapers, documents, food, and other vital items are carried using very small aircraft. However, a large portion of air-freighted goods travels in the bellies of passenger planes. The amount that is flown in bellies can be increased with skilled handling and loading. Also, large-scale aircraft are available such as the giant Antonov. There are many experiments that continue to develop aircraft that could carry a massive amount of freight at lower costs.

It has been predicted that there will be a 50% increase in airline passengers., and air cargo traffic could be reached 150 million tons per year by the year 2030(Gelhausen et al., 2013). The air cargo operators and ground service suppliers are continuously trying to provide a good service at a low cost even though the industry faces severe pressures in high fuel prices, severe competition from other modes of transportation, economic deviations, environmental impacts, etc. If quality is the main priority this balance to strive becomes impossible.

Today, the express market has grown into full cargo and courier or postal operators even integrating with ground network and ocean shipping. The traditional air cargo players are working with various stakeholders, and they are reluctant to invest in modern methods due to low margins. Today, cargo is considered a vital contributor to airlines for cost-effectiveness and total service package. However, outsourcing ground and warehouse handling has become the standard method due to the limitations of policies and cost which made it challenging to preserve profitability (Sales, 2016).

Since the global recession in 2008, the use of freighter aircraft has changed(Cohen et al., 2021). The demand for products fell drastically around the world, and as a result passenger aircraft with high cargo volume were distributed to airlines. Further, specific passenger needs are met with the use of freighters in the charter market.

1.5.3 Air Freight and Supply Chains

Logistics businesses are upgrading their businesses to facilitate new rules, and technologies and for market demands continuously. The e-commerce culture has made tense pressure, especially in the air cargo industry to deliver goods efficiently, and correctly(Stiller, 2003). Technology advancement is broadening pathways and it will increase openness and open up information when required. It is expected that the complete supply chain activity should be 100 percent electronic within the next decade if all new advancements go as planned. The industry should maintain to reduce expenses and cut handling time, also be responsive, innovative and a leader compared with sea transport.

Air transportation creates several unique selling points for the supply chains. Rapid air transportation helps to use Just in Time (JIT) which reduces inventory and expensive warehousing(Panova et al., 2020). The high value of the shipments encourages significant delivery by air to avoid vulnerability to theft, counterfeiting, and sensitivity to temperature. Furthermore, air transport excessively supports for rapid delivery of spare parts for continuous industrial processes varying from simple components to oil drilling replacement tools. Additionally, special considerations are paved for perishables and medicines that require quick and temperature-controlled settings according to health regulations. Significant collaboration and network between suppliers, shippers, and transporters will play an important level in service to satisfy customers.

Since the world faced a major economic downturn in 2008 and many other economic sufferings, natural disasters, and pandemics changed the way the air freight business was reshaped continuously(Demir, 2022). The first thing that we must admit is that while air freight demand is declining, the world has moved with recreational travel. Modern trends suggest that freight capacity is prone to surpass need except something is done to stimulus new business.

1.5.4 Road Feeder Service

Land transport plays a major role in air freight delivery and the air cargo spends only 10%-20% in the air and the rest of the journey happens on land. The time that cargo is on the ground is mainly controlled by ground handling services road transport also involves in most cases(Gelhausen et al., 2013). The road transport between shippers, throughout the process, until it meets the client is one of the significant, costly, and highly possibly delay elements of air logistics. The road feeder service is happening according to different methods, styles, different efficient levels, conditions, and regulations in different regions of the world. The freight for import or export is either delivered or collected for international airports or major hubs and handled with specialized roller bed trucks or unit load devices. For airlines that operate freighters, offers some advantages over road transport. According to Beifert, (2016) 30-45% of the overall quantity of air cargo transshipped by German hubs like Frankfurt and Munich with the use of road feeder service.

1.5.5 Freight Forwarders

The freight forwarders and the forwarding agents play the role of the multifaceted operator that acts between the shipper and the customer following shipments with handling agents and delivering the shipment fast, and in the right condition to the destination. These freight forwarders must be knowledgeable about supply chain management and have a good network to contact with airlines and charter brokers to get the best prices upon negotiation. The forwarder is responsible for the freight, they follow the international regulations in air transport, adhere to dangerous goods regulations and documentation, and then follow up with the cargo ground handler at the airport of departure. Then, at the destination, the respective forwarder will deliver the shipment to the exact customer.

The multinational large freight forwarders may operate their flights and the ground fleet to merge the added freight from different clients. The leading multi-modal IATA forwarders are, DHL, Kuehne &Nagel, DB Schenker, UPS, Sinotrans, Ceva Logistics, Expeditors, Hellmann Worldwide, etc.(Melnyk & Мельник, 2020) These freight forwarders will provide modern services like global data network information, monitoring direct flights, consolidation or break bulking, and door to door or express traffic service, temporary storage, just-in-time deliveries, etc.

The freight forwarder industry depends upon IT systems that allow actual-time position information to be allowed throughout the supply chain. In all the areas of logistics and forwarding the availability of technology guides for efficiency and customer service of all operations.

1.5.6 Cargo Security and Risks

The logistics operators have the responsibility of making the shipments secure and protected when they are moved by air. The operators can mitigate the threats with proper monitoring but, they also unknowingly can create risks too. Mainly during the road transit phase that occurs opportunities for hijacking and theft. The short-distance route can be possibly taken for cost-cutting purposes where one driver will be allocated for the vehicle and the threat of robbery is high during the journey.

1.5.7 Innovation and Trends in Air Freight Industry

The traditional methods of air cargo handling have disappeared with the global e-commerce growth. The millennials and Gen Z has mainly contributed to online purchasing which made the high demand for air cargo. The new e-commerce platforms get benefitted from the changes in consumer behaviors(Melnyk & Мельник, 2020). These companies are highly dependent upon air freight and they are more capital efficient. The factory-controlled e-commerce has impacted the wholesaler, distributors, and retailers to lose from the air cargo logistics chain. Technological advancements have brought the concerns of fast delivery, safety, and security, and fewer damages, in the integrated distribution systems.

The cost of transportation becomes high when the products are air lifted. In such a situation freight forwarder mainly try to reduce the cost of transportation through the land transportation segment that is involved in the distribution network.

1.5.8 Air Freight Distribution and VRP

Air cargo is mainly followed up by the freight forwarders from its customers to the airport and the distribution of air cargo from the destination airport to the doorsteps of customers. Mostly the air cargo is picked from the freight forwarders from the customers and consolidated in their warehouses or depots before they get air transport. Also, the forwarder picks up cargo from the airport and deconsolidate using their warehouses and delivers to customers. In air freight, the feeders have to deliver the freight within a certain time window.

Cheung & Hang, (2010) developed a VRP with backhauls and time window(VRP – TWB) constraints which focus on the fast solution times that can serve by air freight forwarders. Furthermore, they aim to address issues like multiple trips per vehicle, heterogeneous vehicles, and the penalty for early arrivals. A study has discussed the solution method for two issues arising in real-world vehicle routing problems in air freight road feeder service(Derigs et al., 2011). It was aimed to minimize the number of required tractors for the feeder service and the routing methods were used which are currently in practice. Dursun & Özger, (2022) studied a new node based multi-depot heterogeneous fleet VRP with time windows (MDHFVRPTW). The heterogenous fleets include both airlines and vehicles in road transport, using narrow and wide time windows emphasizing quick and usual demand. They used a new hybrid genetic algorithm with variable neighborhood search (HGA- VNS) to retrieve the solution and the proposed MDHFVRPTW and algorithm are expected to deliver a new perspective to transportation.

Nguyen & Phung, (2021) study normal air freight with two objectives minimizing delivery lead time and total shipping cost considering capacitated VRP with time windows (CVRPTW). It was solved by utilizing the adaptive inertia weight particle swarm optimization (AIWPSO) model. Fang & Mao, (2020) examine the efficient handling of cargo containers in an air cargo terminal with the use of an energy-efficient elevating transfer vehicle routing problem (ETVRP). It proposed an exact formulation and developed two approximation algorithms that aim to reduce the energy consumption of elevating transfer vehicles.

The express service of freight is the most prominent usage by air transport. Therefore, with the concerns about express service relying on an air fleet and ground network, H. Li et al., (2019) studied two-echelon VRP with capacity-matching constraints. They considered the cargo assigned to aircraft and then after reaching the destination how the trucks delivered freight to customers. It was developed random sequence algorithm following a variable neighborhood search. It is concerned with surging air cargo demand and using automated freight handling systems with energy-efficient routing for vehicles. Hu et al., (2017) studied ways to minimize energy consumption through vehicle routing of multi-capacity rail-guided vehicles.

1.6 Defining Research Objectives and Questions

Global Value Chains (GVCs) are playing a bigger role in the global economy of trade. The GVC model was first investigated in the context of businesses including transportation equipment and electrical goods in East and Southeast Asia, but it is now increasingly used in other countries and industries. The cause is that companies involved in GVCs maintain very low inventory levels as a cost-cutting tool and rely instead on transporting items swiftly, consistently, and affordably across regions or countries. Given the urgency with which GVCs must move commodities, air freight is seen as a major means of involvement and advancement(Memedovic et al., 2008). Air freight is considerably faster than marine shipping, and express carriers and manufacturers prefer it for the transportation of items with a high value-to-weight ratio, like highly specialized components. The quickness, dependability, and security of air freight are particularly advantageous in situations where land transportation is delayed owing to societal or natural circumstances, in addition to aiding businesses in maintaining minimal inventories.

Most significantly air transport is used because of the requirement to achieve the proper goods at the right time even freight transport from far away locations. In city logistics, consumer behavior is mostly driven by the advent of e-commerce. And mainly demanding speed of service. From this perspective air international transport is vital to fulfilling the expanding needs of rapid distribution from customers.

In general, cargo airlines have a backbone network of flights between hubs, and they maintain ground transportation with the use of specializes partners equipped with the truck fleet to handle cargo. Road freight transportation or road feeder service (RFS) is an important partner connection for logistics chains in air cargo. The transport companies have to deal with complex resource allocation problems and assigning vehicles and drivers. Further, when transporting in city limits the suitable types of vehicles, temperature control techniques, legal regulations on deliveries, on time requirements of the customers has to be fulfilled. In longer distance traveling train or ferry service can be used which operates in a fixed schedule and determine the times of such tasks. Therefore, freight forwarding companies coordinate the freight shipment on behalf of their customers and provide assistant for smooth operation.

Considering the importance of air cargo distribution in city logistics, the studies that have been conducted focusing on air freight distribution within city limits are comparatively fewer. Therefore, this has made a research gap to investigate more air freight within cities and to optimize the distribution network.

There are two main distribution strategies as a single-echelon strategy and a multi-echelon system. In single or direct distribution strategy the freight transports to the delivery point without switching the mode of transportation. In multi-echelon distribution, a shipment of freight travels from its beginning to its finishing point via intermediate locations (satellites, warehouses), where it is first unloaded and then loaded into a similar or a different type of transport unit. In distribution systems commonly the multi-echelon network is used where operations like packing, palletizing, etc. happen. It was presented an overview by (Guastaroba, Speranza, Vigo, et al., 2016)about freight transportation planning with intermediate facilities. The intermediate facilities are great facility locations for different operations in consolidation, value-adding services, break bulking, transshipments and storage. At some of these intermediate locations, the various modes of transportation that are a part of these systems halt, and occasionally the freight switches modes of transportation altogether.

In multi echelon systems, VRP is a basic problem associated with distribution and transportation. In vehicle routing problems, the intermediate facilities functions as the consolidation centers or the transshipment nodes(cross docks) with the aim of reducing transportation costs, and travel distance or enhancing customer service. The more intermediate points create the distribution system complex and can be harder to solve too. Because of these reasons the literature related to these three echelon distribution networks is scarce. But the importance to study the impact of intermediate points on the network should be assessed.

The literature review of the study highlights that optimizing air freight distribution networks and their aspects are rarely investigated under the three echelon distribution networks. According to the above explanations, there are few research gaps identified.

Firstly, it was identified the lack of research with a focus on air cargo distribution in city logistics. And then the scarcity of research focuses on applications in three echelon network and VRP with the concerns of intermediate facilities. Also, it has raised the concern to study how efficiently the routes can be optimized in each echelon to distribute air cargo within a geographic area. Furthermore, the research will focus on the more practical aspect of VRP for three-echelon distribution networks.

1.6.1 Research Questions

RQ 1. *How to optimize each echelon separately, through vehicle routing problem in the air cargo distribution network?*

RQ2. *How to formulate an optimized model for the vehicle routing problem in the three-echelon network?*

RQ3. *How to evaluate the effectiveness of the proposed method and its applicability for a practical scenario in air cargo distribution?*

1.6.2 Research Objectives

Objective 1. *To optimize each echelon separately in the air cargo distribution network, through vehicle routing problem*

Objective 2. *To formulate an optimized model for the vehicle routing problem in the three-echelon network*

Objective 3. *To evaluate the effectiveness of the proposed method and its applicability for a practical scenario in air cargo distribution*

CHAPTER THREE: METHODOLOGY

1.7 Methodologies Used in Three Echelon Distribution Networks

1.7.1 Clustering Analysis

The splitting of things (like items or persons) into groups according to one or more of their properties is the subject of cluster analysis(Anderberg, 1973). In a multidimensional space, a cluster is a collection of connected regions with a comparatively great density of points that are disconnected from other zones of the same type by a region with a comparatively low density of points(R. Zhang et al., 2019).

The above definition of a cluster is a good start for cluster analysis as the first step of recognizing a group of customers in the system of vehicle routing problem. Cluster analysis demonstrates a large collection of grouping techniques that can utilize in heuristic methods related to VRP.

Literature studies have recognized the potential cluster analysis to resolve the Vehicle routing problem. The discovery of clusters of points in the multiple traveling salesman problem was mentioned for the first time by Dantzig & Ramser, (1959b). He stated that anyone can search for clusters of points and can decide through trial and error that they can be traversed while making sure that no loop crosses itself.

Some benefits recognize from the grouping method, such as the earliest decisions can be made such that clients in a particular area will not be served by potential depots located in other regions, and customers can consider as one concentration of demand considering their geographical proximity. With great success, the well-known Clarke-Wright (Clarke & Wright, 1964b)method implements an innovative saving technique to find the proximity matrix. According to Bodin, (1975) creation of groups is a method to approach Routing and Scheduling Vehicles Problems. Furthermore, Madsen, (1983) used Grouping procedures to support solving VRPs. In the development of VRP by Cullen et al., (1981) study, it has used simple grouping procedures. A study has included cluster analysis in VRP distribution and collection techniques (Min, 1989). He has used the group median proximity measure that benefits single linkage and complete linkage. A study considers an LRP heuristic based on grouping methods, identifying a collection of groups using the least spanning tree before refining them using a 1-optimal approach (Srivastava, 1993). In reality, despite the fact that there have been numerous attempts to incorporate grouping strategies into algorithms for the LRP, there have not been any qualified experiments among the various grouping techniques to assess their true capabilities.

1.7.1.1 Proximity Measures

There are several methods that can use to define a closeness between points in a plane. The very conventional quantitative method is the Euclidean metric which can be denoted as follows.

I = (x_i, y_i) and J = (x_j , y_j) therefore, proximity d(I,J) = $\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$

There are some other methods to calculate the proximity among groups based on the above concept, such as the nearest neighbor method, complete linkage, centroid, group average, etc. It has been mentioned that class means, a comprehensive link creates clearer outcomes than nearest neighbor and centroid(Blashfield & Aldenderfer, 1988). Additionally, in each scenario, the method should be carefully chosen and with several tests, the correct method can be selected.

1.7.2 Clustering-Based Heuristic Approach

We discuss mixed integer linear programming formulations for the three-echelon VRP in the arc-based formulation.

To establish a group of transportation routes in the network, a clustering algorithm is one of the most useful techniques. The main purpose of the clustering algorithm is to divide demand nodes into clustered groups and then solve delivery routes for each group(Yücenur & Demirel, 2011). One of the main advantages is that it will simplify the network to solve easily. The number of decision variables related to customer nodes will be less and the number of constraints for vehicle routing will be minimized (Drexl & Schneider, 2015).

In literature studies, the clustering-based heuristic method has been discussed. To solve the multi-objective location routing problem C. K. Y. Lin & Kwok, (2006) used a clustering-based metaheuristic method. Firstly, the ratio of total demand to facility capacity is used to determine the minimal number of facilities necessary. Then they ranked the facilities according to which were closest to the customer sites. They then used the Greedy technique to choose the collection of facilities. Secondly, they created the routes by different versions of the saving algorithm and the use of the nearest neighbor rule. Furthermore, according to customer demand and vehicle capacity, Nadizadeh & Hosseini Nasab, (2014) implemented the greedy-based algorithm to cluster customers. They ranked the depots according to their capacity and a fixed opening cost equation in the allocation step. Then, the distance from the gravity center of each client cluster to the top-ranked depot was calculated. The authors used the ant colony method to solve the problem by focusing on each cluster's route. Furthermore, a study based on the fuzzy demand of capacitated location routing problem was conducted by Zare Mehrjerdi & Nadizadeh, (2013) using a hybrid heuristic method and Ant Colony optimization. Additionally, a study conducted by Kchaou Boujelben et al., (2014) based on the Clustering method was used in the LRP problem that applied the mixed integer programming and introduced minimum volume constraints. To simplify the process of assigning each client to newly opened distribution centers, the original challenge was changed to simply involve a representative-specific route.

Most studies identified each member of each cluster during the clustering stage by the proximity of the customers and the vehicle capacity. Essentially, Euclidean distance is based on multiple proximity metrics to generate the closeness distance according to research literature. According to the computational point of view, sequential methods are more suitable for the VRP with the fixed cost of distribution and the limited carrying capacity of vehicles .

Sequential Heuristic used for the VRP

Input: Coordinates N number of customers with their demand values

Coordinates potential satellites with capacity and the operational costs of satellites

Output: Vehicles paths constructed in Satellites

Step 1: build clusters of customers with the demand and capacity control

Step 2: Find the delivery route in each customer group

Step 3: Make the necessary improvements to the routes

Step 4: Place the satellites and assign the routes to them

1.8 Case Study: Three-Echelon Air Freight Distribution Network

We considered an initial air cargo distribution network constitute of the airport, three warehouses, and directly serve to the customers using the fleet of vehicles. Our case study is about a freight forwarding company in Sri Lanka that provides transportation, warehousing, and other logistics operations for customers. The company requires to redesign the current distribution network to reduce the total transportation cost of the network. Our new proposed case study network consists of one airport, 3 depots, and 9 satellites and expects to serve the designated 100 customers. Figure 1 shows the schematic diagram of the considered three echelon network.

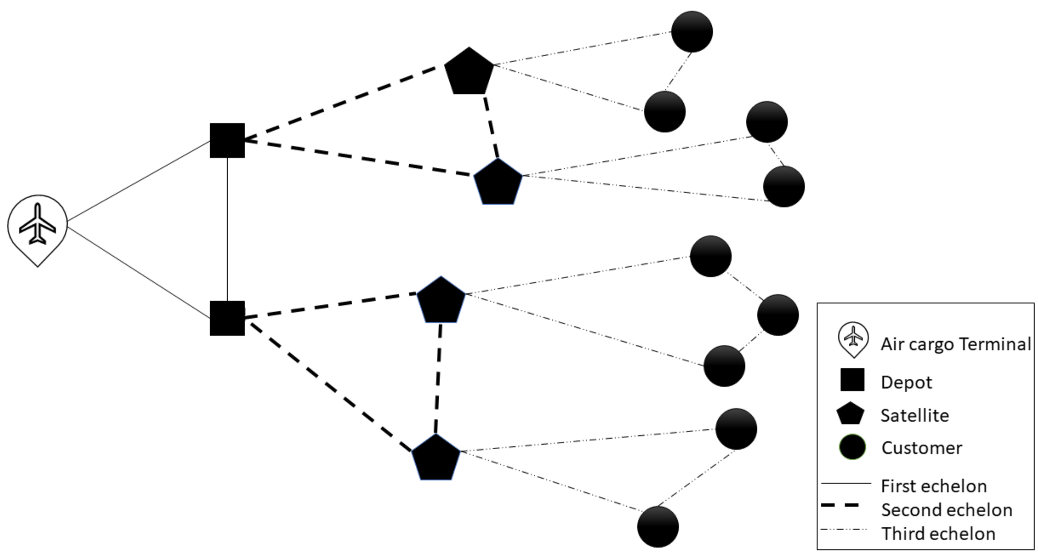


Figure 1 Schematic diagram of three echelon network

1.8.1 Coding Principle

In this distribution network, we have considered one particular type of commodity. Based on a coding principle introduced by G. Laporte we represent our problem as 4/T/T/T. The number 4 represents layers of the distribution network. There are four layers including three layers of facilities and one layer of customers. The three facility layers are the airport, depots, a set of satellites, and the customers at the final layer. Additionally, there are three echelons of transport routes that connect between the adjacent layers as denoted T/T/T. T stands for tour trip and in all three echelons, the vehicles circulate air freight from starting facility and distribute it to each node and return to the same starting node.

1.8.2 Clustering Procedure

The clustering-based approach is applied to resolve the VRP to reduce the computation time and to have an efficient solution. The nearest Neighbor Algorithm is used to cluster the number of nodes. We used to cluster the demand nodes to the respective satellites. It starts by identifying the first node and then the nearest node and grouping them into the same cluster. The clustering procedure can be described as follows.

1. The initial clustering is done by assigning a customer to its nearest satellite according to the travel distance.

2. The assignment then should be feasible concerning the fleet-size restriction.

3. The customer is sent to the second closest satellite if the initial assignment is unworkable, and so on until a workable assignment is found.

4. For the new clusters, resolve the little independent VRPs if not.

5. Update each satellite's demand following the new assignment, then resolve the following VRP.

The solution approach will be a clustering-based heuristic approach (Crainic et al., 2011). Firstly, the clustering procedure will be followed and then it will solve for Vehicle routing problem. The data was sourced from a freight forwarder company and few literature studies were used to recreate them. We present the results of a computational test of the VRP using the proposed model. Python 3.7 was used to solve the arc-based formulation and VRP. We show computation time to show the performance of our algorithms.

1.8.3 A Heuristic Method for Case Study

According to the literature studies, the most suitable method is the heuristic approach. In the heuristic method, the clustering-based algorithm is appropriate to solve the case study.

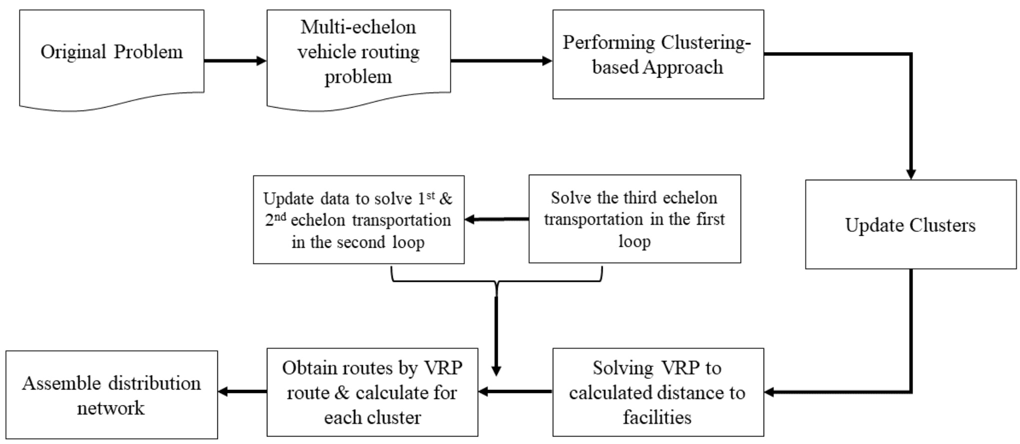


Figure 2: Main proposed solution method for three-echelon VRP

Firstly, the original problem is identified. Then we perform cluster first route second concept to create the transportation routes for the third echelon. Then the customer clusters and the demand of each customer cluster in the third echelon are considered when allocating them to the satellites. This allocation is considered an update to solve the second echelon and then those updated demands will use for the first echelon. The original VRP is applied in this research, and it has been modified accordingly to the constraints we focus. We have formulated using mixed integer linear programming.

To solve the three-echelon VRP we construct the 3rd echelon transportation routes first and then identify the satellites and depots assigned to serve the customer nodes. Before creating the second echelon transportation route, it is critical that the demand of clustered clients in the third echelon is accumulated to the relevant satellite. After the entire steps are done we obtain routes and transportation costs from all the echelons and combine all parts to form a complete distribution network.

1.8.3.1 Clustering-based Approach

According to the literature studies, both iterative methods and hierarchical methods can provide a better solution than the clustering technique. But the computation times can be significantly longer. Therefore, the study is aiming to use a sequential clustering-based approach to solve three-echelon VRP to minimize computation time. These phases have used the methods used by Kchaou-Beljeben et al., (2014) and redeveloped according to the conditions of the problem.

1.8.3.1.1 Initial Grouping Algorithm

The initial group algorithm aims to reduce the size of the search space by using facility location as the reference to build the initial group. Firstly, it identified the dispersed facility locations over the distributed zone and identified the demand location, and check for their closeness to the satellites. The main attribute of the algorithm is the coverage distance which means the area where customers and the satellites are connected. Therefore, we determined a suitable coverage distance by varying the specific average distance. The initial grouping algorithm is presented here.

Parameters: customer demand nodes & airport, depot, and satellite nodes, demand order weight amount, facility capacity, coverage distance, and distance between each node from a distance matrix.

Step 1: compute the number of facilities (Satellites) that derive from the ratio of the total demand of customers to the average facility capacity

Step 2: Identify the relevant customer demand nodes assigned to each satellite, which satisfies the coverage distance. Then sort the satellites in descending order according to the average distance from each satellite to its member customers.

Step 3: Then select a satellite that shows minimum average distance and then all the customer nodes will be used for the next step

Step 4: Revise the average distance between the satellites and the member demand nodes, eliminating the demand nodes that have already been put into a group.Repeat steps 2 and 3 for the rest of the satellites and customer nodes

Step 5: To confirm that every customer is assigned to the nearest satellite it can swap each customer demand node to the nearest satellite facility.

Step 6: Finally, assign any unassigned demand nodes outside of the coverage area to the closest available facility if they exist.

1.8.3.1.2 Clustering Algorithm

This algorithm is chosen with the purpose of creating a cluster of transportation routes. The transportation routes will be built for both satellite and customers and the obtained clusters from the initial grouping phase will be used here. Exact techniques are tough to solve, and this method is helpful because of the efficient answers and shorter computing times.

The nearest Neighbor Algorithm is commonly used to solve Travel Salesman Problem but is used to cluster the member of nodes(Bellmore & Nemhauser, 1976). We use this method to group the demand nodes into clusters identifying the first node and then the nearest second node and will continue to cluster. Further before feeding the findings to the following phase, we additionally modify the exchange algorithm to improve the cluster of transportation routes in terms of shorter distances. In order to avoid grouping together nodes with huge customer demands, which makes it impossible to assign the facilities, we establish the permitted demand amount per cluster.

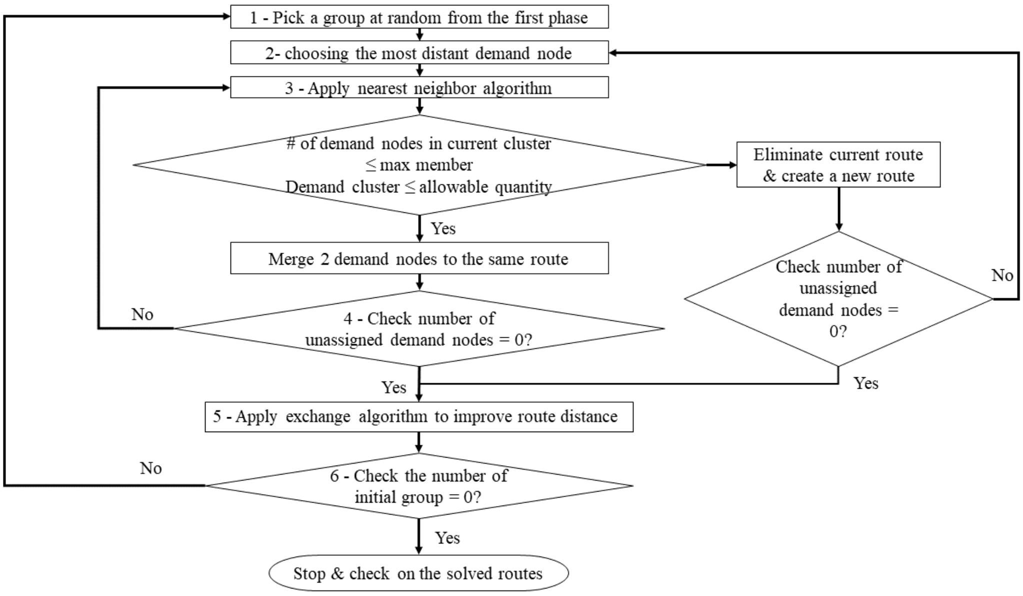


Figure 3: Clustering algorithm

According to the above clustering algorithm, the first step is to randomly select from the previous grouping method. Secondly the most distant node from the satellites of the chosen group. Then thirdly, the NNA method was performed. It chose the nearest customer node adjacent to the most recent member node, and the cluster grew to include the customer demand node. This can happen only if the following situations are fulfilled.

- There are fewer cluster members than permitted at the drop point
- The entire demand does not exceed the permitted demand level.

The preceding second and third stages should then be repeated until no customer nodes remain. By exchanging customer nodes between the many clusters that are close to one another, the transportation route's quality can be improved(Derigs & Reuter, 2017). Then repeat the first, second, and third steps until all initial groups are solved. Chapter 3 has presented the methodology to address and solve the research questions of the study. The clustering-based heuristic technique and grouping analysis used in this work have been reported. Research outcomes described in Chapter 4 explicitly.

CHAPTER FOUR: RESULTS AND DISCUSSION

In this section, the mathematical model of the three-echelon distribution network and the result of the solved case study is described explicitly.

1.9 Arc Based Mathematical formulation

The mathematical formulation for 3E-VRP for the air cargo distribution network is demonstrated.

The 3E-VRP is described on a directed graph G = (V, A) where vertex set V consists of airport P, a set of depots D, a set of satellites S, and a set of customer C. The air freight from the airport will be transported by a homogeneous fleet of FE vehicles to depots, from depots to satellites will be transported by the SE vehicle fleet, and from satellites to customers TE, a homogenous vehicle fleet will be used to distribute. Sets K_1, K_2, and K_3 represents FE, SE, and TE vehicles. The FE, SE, and TE vehicles have capacities in Q_1, Q_2, and Q_3.

The arc set A of graph G can be divided into three separate sets of FE arcs $A_1 = \{(i, j)|i, j \in P \cup D,\ i \neq j\}$ connecting the airport and depots, SE arcs $A_2 = \{(i, j)|i, j \in D \cup S,\ i \neq j\}$ connecting depots and satellites and TE arcs $A_3 = \{(i, j)|i, j \in S \cup C,\ i \neq j\}$ connecting satellites and customers. The FE arcs in A_1, SE arcs in A_2, and TE arcs in A_3 can only be navigated by vehicles in K_1, K_2, and K_3, correspondingly. A nonnegative travel cost C_{ij} relates to each arc (i, j) ∈ A.

There is a maximum of M_s number of SE vehicles leave from a satellite. A non-negative fixed cost in each fleet assigned for each echelon is denoted by h_s, h_d, h_c.

d_i denotes each customer i demand. This need must be met by a single TE vehicle delivery. The FE vehicles are generally thought to have a bigger capacity than the SE vehicles ($Q_1 > Q_2$) and the capacity of SE vehicles is greater than that of TE vehicles ($Q_2 > Q_3$).

Each customer's demand is smaller than what the TE vehicle can handle ($d_i < Q_3$ for $i \in C$). Finding a set of routes for each echelon that reduces the overall transportation cost is the fundamental goal of the 3E-VRP. Further, the routes must satisfy all consumer requests while taking into account vehicle and satellite capacity restrictions. Furthermore, we assume the overall amount of freight that is sent to a satellite should match the total amount of consumers that the satellite serves.

There are two types of decision variables. Binary routing variables $X_{ijk} \in \{0, 1\}$ denote whether a vehicle $k \in K_1$ navigates arc $(i, j) \in A_1$ in first echelon. Similarly, it applies to the second echelon with Y_{ijk}. Integer variables U_{dk} , $U_{sk} \in Z+$ record the location of depot $d \in D$ in the path presented by vehicle $k \in K_1$ and the location of satellite $s \in S$ along the path taken by vehicle $k \in K_2$. The volume of cargo brought from the airport to depot $d \in D$ by vehicle $k \in K_1$ and depot to satellite $s \in S$ by vehicle $k \in K_2$ is represented by W_{dk}, $W_{sk} \in R+$ respectively. In the third echelon binary routing variable $Z_{ijk} \in \{0, 1\}$ denotes whether a vehicle dispatched from satellite $s \in S$ traverses arc $(i, j) \in A_3$. Continuous flow variables f_{ijd}, $f_{ijs} \in R+$ are used to monitor this vehicle's load. Furthermore, the following notations are used to develop the time constraint

p_{ik} = the starting delivery time of vehicle k of K_3 at customer i.

q_{ik} = latest delivery time of vehicle k of K_3 at customer i.

L_i = Service time of vehicle at customer i.

T_{ijk} = The duration of the trip using vehicle type k between nodes i and j

L_{iK3k} = The starting service time of vehicle k of type K_3 at customer i

Assumptions:

- Each depot, satellite, and customer node are known.
- Each consumer node's demand is distinct and cannot be split.
- The fleet of vehicles is known, and they may be found at satellite nodes, depot nodes, and the airport.
- The company’s resource and investment costs are not considered.
- The vehicles dispatched from the airport, depot, and satellites come back to the same origin
- The fleet FE,SE,TE are homogeneous.

- The same commodity type has been considered.
- Each depot and satellite can be visited by several FE, and SE vehicles. For the third echelon, each customer is visited by at most one vehicle.
- FE, SE vehicle visits each depot at most once (per day)
- This is a deterministic model.

Objective:

Minimize total transportation cost:

$$\sum_{k\in K_1}\sum_{(i,j)\in A_1} C_{ij}x_{ijk} + \sum_{k\in K_2}\sum_{(i,j)\in A_2} C_{ij}y_{ijk} + \sum_{s\in S}\sum_{(i,j)\in A_3} C_{ij}z_{ijs} + \sum_{d\in D,k\in K_1} h_{kd} + \sum_{s\in S,k\in K_2} h_{ks} + \sum_{c\in C,k\in K_3} h_{kc}$$

The C_{ij} represents the non-negative travel cost associated with each arc (i,j) ∈ A. A non-negative fixed cost in each fleet assigned for each echelon is represented by h_{kd}, h_{ks}, h_{kc}. The light motor lorry is one of the vehicle kinds utilized on the road as also, as a mini truck, and cargo van. The sum of the fixed cost of the vehicle, the cost of the driver or other labor costs, and the cost of fuel constitutes the non-negative fixed cost costs of the various vehicle types employed in road freight transportation. In this study, the fixed cost components are considered within the total fixed cost. These costs are occurred depending on the vehicle's assignment. Equation (1) shows the total cost components.

h_{ki} = Fixed cost of vehicle + Driver cost + Cost of fuel (1)

The following shows the constraints developed for the first echelon. constraint (1.1) to make sure that each FE vehicle is flow-conserving at each depot. Constraint (1.2) to ensure FE vehicle visits each depot at most once (per day). Constraint (1.3) is to eliminate sub-tours. Constraint (1.4) demonstrates that the flow from the airport to depot d ∈ D by vehicle k ∈ K_1 can only be positive if vehicle k ∈ K_1 is used. The capacity constraint for the FE vehicle is constructed by (1.5). Constraint (1.6) is to link the first and second echelons and mandate that the entire flow be made from the airport to the depot d ∈ D equals the total demand served from depot d ∈ D. Constraint (1.7) is to limit the number of FE vehicles leaving each airport. Constraint (1.8) is to demonstrate that each airport has allocated a specific number of depots.

$$\sum_{(i,j)\in A_1} x_{ijk} = \sum_{(j,i)\in A_1} x_{jik} \qquad i \in P \cup D,\ k \in K_1 \qquad (1.1)$$

$$\sum_{(i,j)\in A_1} x_{ijk} \leq 1 \qquad i \in P \cup D,\ k \in K_1 \qquad (1.2)$$

$$U_{ik} - U_{jk} + |D| x_{ijk} \leq |D| - 1 \qquad i, j \in D,\ i \neq j,\ k \in K_1 \qquad (1.3)$$

$$W_{dk} \leq Q_1 \sum_{(j,d)\in A_1} x_{jdk} \qquad d \in D,\ k \in K_1 \qquad (1.4)$$

$$\sum_{d\in D} w_{dk} \leq Q_1 \qquad d \in D,\ k \in K_1 \qquad (1.5)$$

$$\sum_{k\in K_1} w_{dk} = \sum_{(d,j)\in A_2} f_{djd} \qquad d \in D \qquad (1.6)$$

$$\sum_{(p,j)\in A_1} X_{pjp} \leq M_p \qquad p \in P \qquad (1.7)$$

$$\sum_{k\in K_1} p_i = N_j \qquad \mathrm{j} \in D \qquad (1.8)$$

constraint (2.1) to make sure that each SE vehicle is flow-conserving at each depot. Constraint (2.2) to ensure SE vehicle visits each depot at most once (per day). Constraint (2.3) is to eliminate sub-tours. Constraint (2.4) demonstrates that the flow from the depot to satellite s ∈ S by vehicle k ∈ K_2 can only be positive if vehicle k ∈ K_2 is used. The capacity constraint for the SE vehicle is constructed by (2.5). Constraint (2.6) is to ensure that the overall flow from the depot to the satellites is equivalent to the total demand met by the satellites by connecting the second and third echelons. Constraint (2.7) is to limit the number of SE vehicles dropping at each airport. Constraint (2.8) is to demonstrate that each airport has allocated a specific number of satellites.

$\sum_{(i,j)\in A_2} y_{ijk} = \sum_{(j,i)\in A_1} x_{jik}$ $\quad i \in D \cup S,\ k \in K_2$ *(2.1)*

$\sum_{(i,j)\in A_2} y_{ijk} \le 1$ $\quad i \in D \cup S,\ k \in K_2$ *(2.2)*

$U_{ik} - U_{jk} + |S| y_{ijk} \le |S| - 1$ $\quad i, j \in S,\ i \ne j,\ k \in K_2$ *(2.3)*

$W_{sk} \le Q_2 \sum_{(j,s)\in A_1} x_{jdk}$ $\quad s \in S,\ k \in K_2$ *(2.4)*

$\sum_{s\in S} w_{sk} \le Q_2$ $\quad s \in S,\ k \in K_2$ *(2.5)*

$\sum_{k\in K_2} w_{sk} = \sum_{(s,j)\in A_3} f_{sjs}$ $\quad s \in S$ *(2.6)*

$\sum_{(d,j)\in A_2} y_{djd} \le M_d$ $\quad d \in$ D *(2.7)*

$\sum_{k\in K_1} D_i = N_j$ $\quad$ j $\in S$ (2.8)

For the third echelon, we developed a separate number of constraints. Constraint (3.1) ensures conservation of flow at each TE node. Constraint (3.2) reduce the number of TE vehicles dropping each satellite. Constraint (3.3) is to guarantee that each customer is visited exactly once. Constraint (3.4) suggests that the customer demands are met and forbid the presence of sub-tours. Then, constraint (3.5) is the capacity constraint for the TE vehicles. The time flow constraints are represented by (3.6) and (3.7). The constraint which defines each consumer will be served throughout their designated time windows is demonstrated by the equations (3.8) and (3.9). Constraints (3.6) – (3.9) were created as per the study of Toth et al., (2014).

$\sum_{(i,j)\in A_3} Z_{ijs} = \sum_{(j,i)\in A_3} Z_{jis}$ $\quad i \in S \cup C,\ s \in S$ *(3.1)*

$\sum_{(s,j)\in A_3} Z_{sjs} \le M_s$ $\quad s \in S$ *(3.2)*

$\sum_{s\in S} \sum_{(i,j)\in A_2} Z_{ijs} = 1$ $\quad j \in C$ *(3.3)*

$\sum_{s\in S} \sum_{(i,j)\in A_3} f_{jis} - \sum_{s\in S} \sum_{(i,j)\in A_3} f_{jis} = d_i$ $\quad i \in C$ *(3.4)*

$f_{ijs} \le Q_2 Z_{ijs}$ $\quad (i.j) \in A_3,\ s \in S$ *(3.5)*

$L_{iK3k} + \left(L_i + T_{ijk}\right)Z_{ijk} - L_{iK3k} \leq \left(1 - Z_{ijk}\right)M$ $\forall i, j = m + 1, \ldots, m + n, i \neq j, \forall k \in K_3$

(3.6)

$L_{jK3k} + \left(L_j + T_{jsk} - q_{ik}\right)Z_{jk} \leq \left(1 - Z_{jk}\right)M$ $\forall k \in K_3, j = m + 1, \ldots, m + n, i \neq j$

(3.7)

$p_{ik} \sum_{j=m+1, j \neq i}^{m+n} Z_{ijk} \leq L_{iK3k}$ $\forall i, \forall j, \forall k \in K_3$

(3.8)

$L_{iK3k} \leq q_{ik} \sum_{j \neq i}^{m+n} Z_{ijk}$ $\forall i, \forall j, \forall k \in K_3$

(3.9)

1.10 Case Study

1.10.1 Data Collection

We considered a freight forwarding company in Sri Lanka which provide logistics service to their customers. Air freight was considered in this research and obtained the information accordingly. The data were hypothetically created upon the information gained from some expert inquiries from renowned freight forwarding companies and SriLankan Cargo.

Mainly the data focus on the air freight that has to distribute within a day and 100 customers have been considered. The delivery period is 24 hours from the airport to depots and from depots to satellites. And the delivery is happening to the customers during the period of 9 am to 6 pm within a day. In terms of costs, a few cost components have been considered such as the fixed cost of a vehicle, driver cost, and cost of fuel. Then the variable cost is the travel cost which incurs according to the distance that vehicles travel. Customer data also considered the number of customers and the demand of each customer. Further location data are formulated with geographical locations and their longitude and latitudes. Vehicle fleet capacities are also included as per the information. The fleet of light motor lorries with 3000kg weight used for the first echelon, then a fleet of mini trucks with 1000kg used for the second echelon, and the third echelon a fleet of cargo vans with 200kg capacity will be used. Furthermore, the time windows the delivery should happen have been considered. We use starting delivery time, the latest delivery time, and the service time as the inputs for the case study. Service time is a forecasted one depending on the number of packages, and package items, and according to past data.

1.10.2 Case Study and Results

The work designs the distribution network of a freight forwarding company solving the network considering different zones for ease of computation. We solve for zone 1, zone 2, and zone 3. First, we test all problems with normal demand patterns collected from the database.

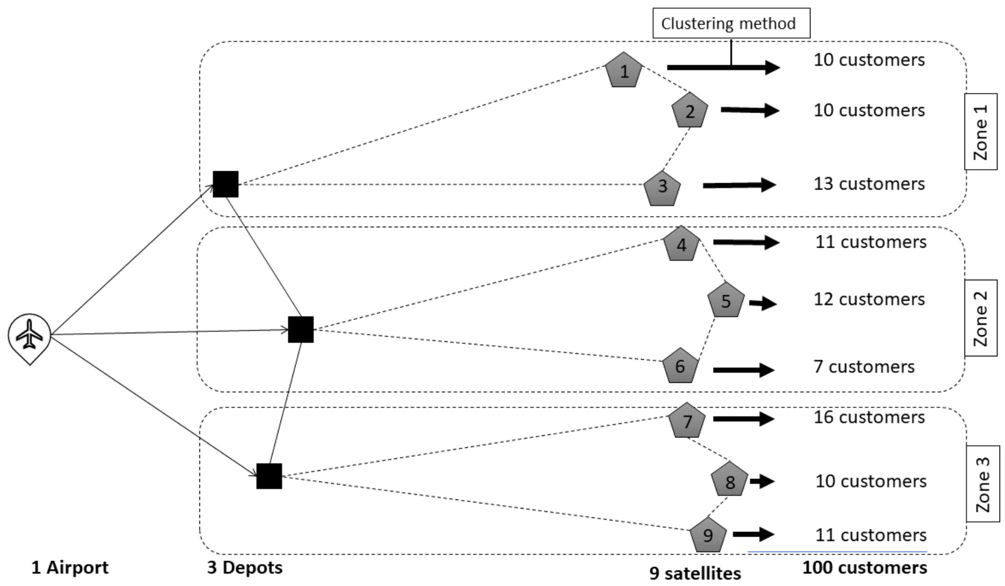


Figure 4 Redesigned distribution network after using the clustering method

Figure 2 shows the three zones that we have considered for the solution approach after using the clustering methods. The zones were considered including each depot separately, their assigned satellites, and the customers that have been assigned using the methodology. These 3 zones would be helpful when the number of customers gets increased, and it will be an easy approach to solve the network. We used these zones when evaluating the feasibility of different scenarios for the same distribution network.

Then we perform scenario analysis for all problems by varying the number of customers, vehicle fleet size, and travel time. These will prove whether or not the solutions of the proposed VRP are robust.

1.10.3 Experimental Results

All tests were performed using Python programming language on a PC with an Intel Corei5-7200U processor (2.50 GHz) and 8.00 GB of RAM. Python programming language has been used to retrieve the solutions and the PyCharm computer program is used as the Integrated Development Environment for code problems.

The classical VRP problem is an NP-hard problem and all the subvariants are also NP. This indicates that no deterministic algorithm exists that provides an optimal solution within the computing time.

The vehicle routes for each echelon have been developed separately with the use of VRP. The problem is a capacitated VRP with time windows. The capacities are given following a homogeneous fleet of vehicles in each echelon. The time windows for the three echelons also have been considered. For the first echelon, the time window has considered 24 hours and for the second echelon also time window is 24 hours. In the third echelon, there are specific hard time windows for each customer to get delivered their freight. Also, it has been considered that the delivery should happen between 9 am to 6 pm within a day.

1.10.3.1 The Solved Vehicle Routes

The clustering-based heuristic method was used to solve the model and obtained the following routes for each echelon.

Firstly, it has shown here the identified route for the first echelon. And the routes from depots to respective satellites.

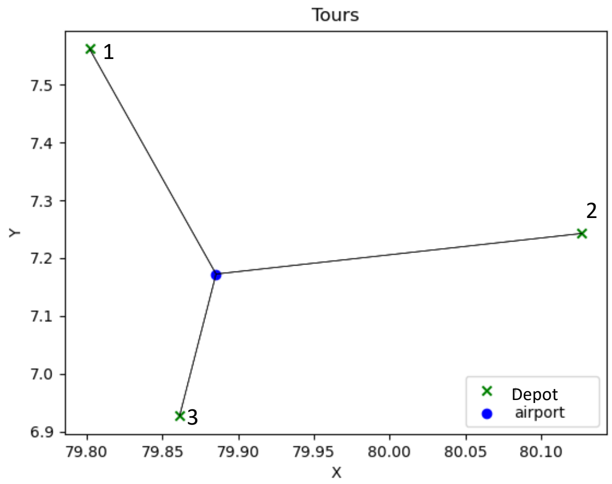


Figure 5: Solved route for first echelon

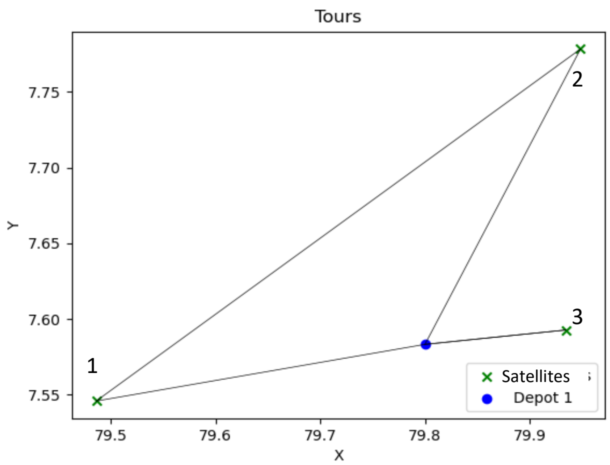


Figure 6: Solved route from depot 1 to satellites

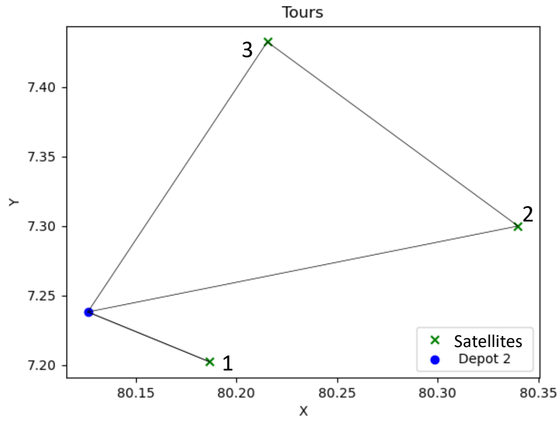


Figure 7: Solved route from depot 2 to satellites

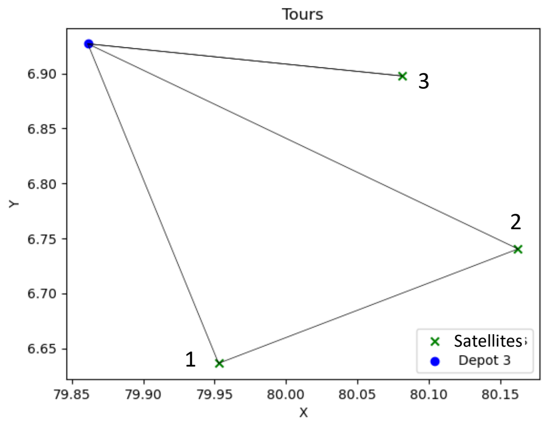


Figure 8 : Solved route from depot 3 to satellites

The following graphs show the vehicle routes of the fleets that have been assigned to the third echelon of all the zones. We have presented the results obtained from solving the VRPs.

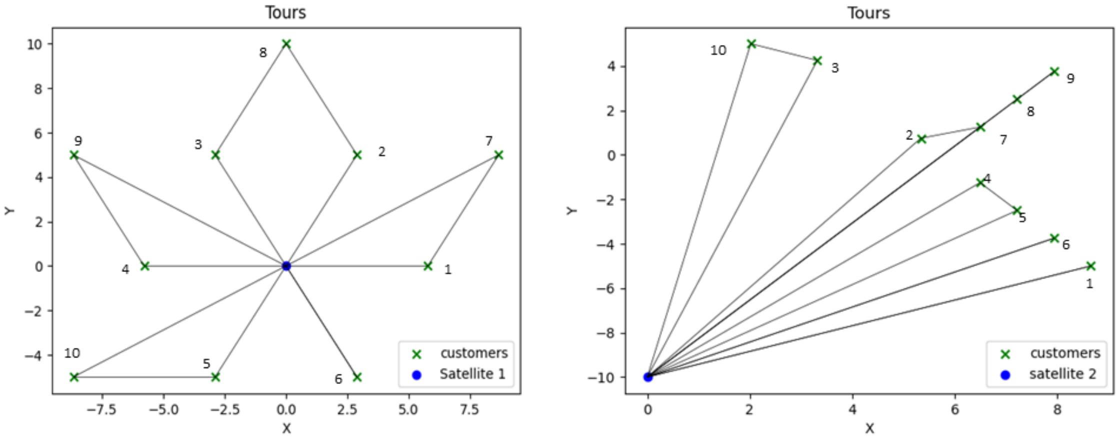


Figure 9: Solved route for vehicle fleet from satellite 1 & satellite 2 to customers

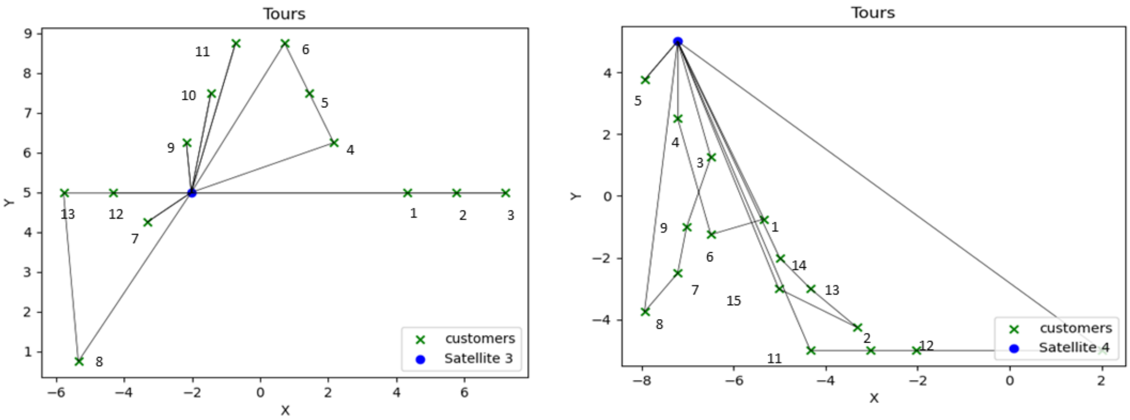


Figure 10: Solved route for vehicle fleet from satellite 3 & satellite 4 to customers

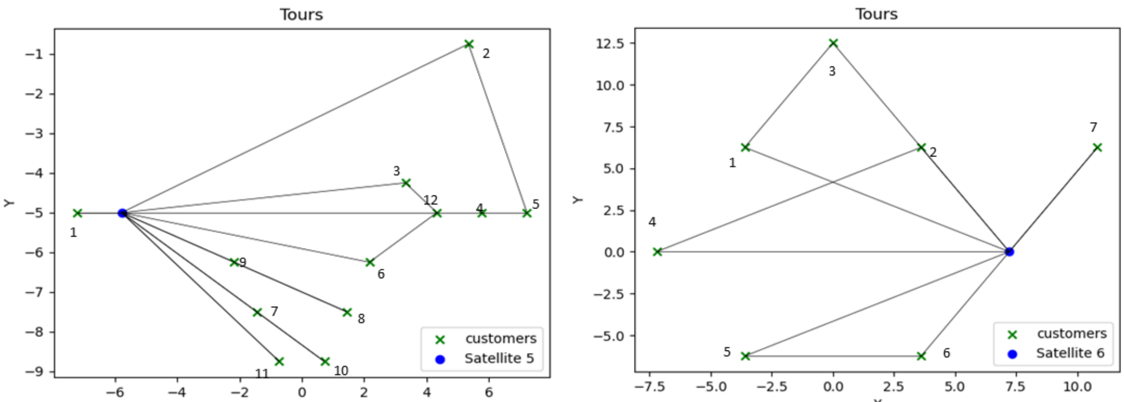


Figure 11: Solved route for vehicle fleet from satellite 5 & satellite 6 to customers

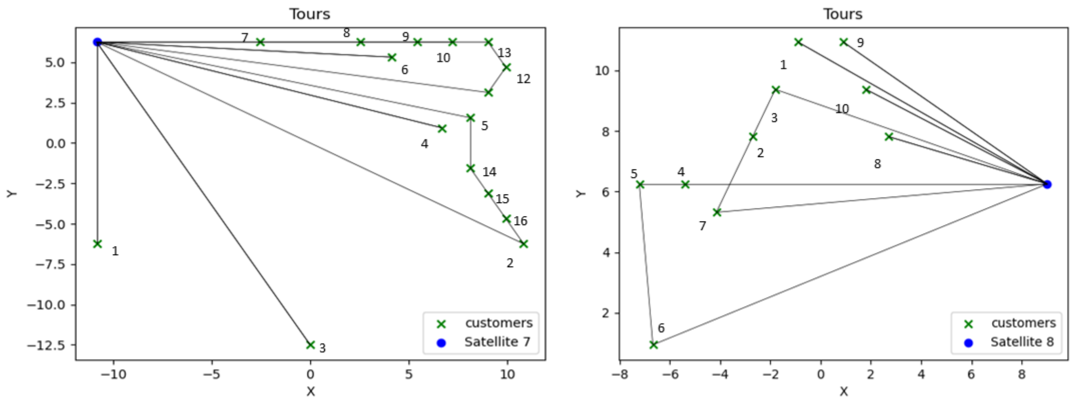


Figure 12: Solved route for vehicle fleet from satellite 7 & satellite 8 to customers

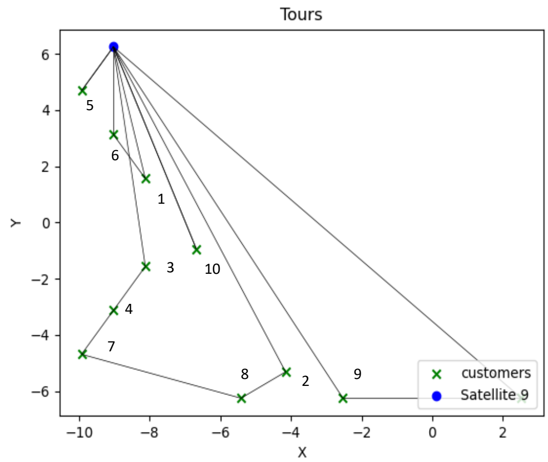


Figure 13: Solved route for vehicle fleet from satellite 9 to customers

The following table gives a summary of the routes that have been solved using the clustering-based heuristic approach and the use of Python programming language.

A represents the Airport, D represents the depots, S represents the satellites, and C represents the Customers. The satellites and numbers are identical to each route though they have been named in similar notations.

Table 1: Summary of the solved vehicle routes

Starting node	Ending node	Number of ending nodes	Number of fleet vehicles	Vehicle routes
Airport	Depots	3	3	A-D1-A A-D2-A A-D3-A
Zone 1				
Depot 1	Satellite	3	2	D1-S1-S2-D1 D1-S3-D1
Satellite 1	Customers	10	5	S1-C1-C7-S1 S1-C2-C8-C3-S1 S1-C4-C9-S1 S1-C5-C10-S1 S1-C6-S1
Satellite 2	Customers	10	6	S2-C3-C10-S2 S2-C2-C7-S2 S2-C8-C9-S2 S2-C4-C5-S2 S2-C6-S2 S2-C1-S2
Satellite 3	Customers	13	8	S3-C1_S3 S3-C2-C3-S3 S3-C4-C5-C6-S3 S3-C9-S3 S3-C10-S3 S3-C11-S3 S3-C7-S3 S3-C8-C12-C13-S3
Zone 2				
Depot 2	Satellite	3	2	D2-S1-D2 D2-S2-S3-D2
Satellite 4	Customers	11	5	S4-C1-C6-C4-S4 S4-C15-C2-C13-C14-S4 S4-C3-C9-C7-C8-S4 S4-C5-S4 S4-C11-C10-C12-C16-S4

Satellite 5	Customers	12	6	S5-C1-S5 S5-C2-C5-C4-S5 S5-C3-C12-C6-S5 S5-C9-C8-S5 S5-C7-C10-S5 S5-C11-S5
Satellite 6	Customers	7	4	S6-C1-C3-S6 S6-C4-C2-S6 S6-C7-S6 S6-C5-C6-S6
Zone 3				
Depot 3	Satellite	3	2	D3-S1-S2-D3 D3-S3-D3
Satellite 7	Customers	16	10	S7-C1-S7 S7-C3-S7 S7-C4-S7 S7-C6-S7 S7-C7-S7 S7-C8-S7 S7-C9-S7 S7-C10-S7 S7-C5-C14-C15-C16-C2-S7 S7-C13-C12-C11-S7
Satellite 8	Customers	10	6	S8-C1-S8 S8-C10-S8 S8-C9-S8 S8-C8-S8 S8-C3-C2-C7-S8 S8-C4-C5-C6-S8
Satellite 9	Customers	11	5	S9-C1-C6-S9 S9-C5-S9 S9-C10-S9 S9-C3-C4-C7-C8-C2-S9 S9-C1-C6-S9 S9-C9-C11-S9

Furthermore, we have obtained the above vehicle routes adhering to the constraints while obtaining the total transportation costs. The below table indicates the total transportation expense of the network and the transportation costs incurred in the echelon.

Table 2: Transportation costs incurred at each node

Routes	Number of Customers	Number of fleet vehicles	Total Demand (kg)	Transportation cost (LKR)	CPU time (ms)
satellite 1	10	5	660	15964.12	80
satellite 2	10	6	750	18611.49	160
satellite 3	13	8	940	17349.91	220
satellite 4	11	5	780	21265.54	980
satellite 5	12	6	865	17809.95	900
satellite 6	7	4	590	13483.43	80
satellite 7	16	10	780	34167.46	190
satellite 8	10	6	710	17837.51	180
satellite 9	11	5	700	16747.69	670
	Number of Satellites	Number of fleet vehicles	Total Demand (kg)	Transportation cost (LKR)	CPU time(s)
depot 1	3	2	2350	4107.95	20
depot 2	3	2	2235	4060.69	80
depot 3	3	2	2190	4107.01	20
	Number of Depots	number of fleet vehicles	Total Demand (kg)	Transportation cost (LKR)	CPU time(s)
airport	3	3	6775	4179.32	20

Per Day Total Transportation Cost	**189692.1**	**3600**

The above table represents the total transportation cost per day for the distribution of air freight in the network using the vehicle fleet. We have evaluated the total transportation costs for each satellite, depot, and airport separately as well.

Table 3: Transportation costs in each zone

	Facilities in Zones	**Number of customers in each zone**	**Total transportation costs in each zone (LKR)**	**CPU time (ms)**
Zone 1	Depot 1 Satellite 1 Satellite 2 Satellite 3	33	56033.47	480
Zone 2	Depot 2 Satellite 4 Satellite 5 Satellite 6	30	56619.61	2040
Zone 3	Depot 3 Satellite 7 Satellite 8 Satellite 9	37	72859.67	1060

The above table shows the transportation costs of each zone and the CPU time it takes to calculate the total route network. The highest transportation cost shows from zone 3 mainly because the highest number of customers in the zone is higher than in the other zones.

The following table shows the delivery starting time obtained according to the proposed model. The customer's preferred period and service time of the delivery has been considered when obtaining the delivery starting time. All the delivery services start at 9 am and delivery will happen until evening 6 pm.

Table 4: Delivery start time for every customer in minutes

	Customers	Customer's preferred time period	Delivery start time for every customer in minutes (obtained from model)	Delivery Starting Time
Satellite 1	1	10:00-13:00	60	10:00
	2	13:00-16:00	240	13:00
	3	11:00-14:00	120	11:00
	4	15:00-17:00	360	15:00
	5	9:00-13:00	0	9:00
	6	10:00-16:00	60	10:00
	7	11:00-15:00	120	11:00
	8	12:00-15:00	180	12:00
	9	14:00-17:00	300	14:00
	10	9:00-10:00	0	9:00
Satellite 2	1	10:00-13:00	60	10:00
	2	9:00-10:00	0	9:00
	3	11:00-12:00	120	11:00
	4	15:00-18:00	360	15:00
	5	9:00-12:00	0	9:00
	6	10:00-16:00	60	10:00
	7	9:00-13:00	0	9:00
	8	11:00-13:00	120	11:00
	9	14:00-17:00	300	14:00
	10	10:00-11:00	60	10:00
Satellite 3	1	10:00-13:00	60	10:00
	2	10:00-11:00	60	10:00
	3	9:00-14:00	0	9:00
	4	15:00-17:00	360	15:00
	5	9:00-13:00	0	9:00
	6	10:00-16:00	60	10:00
	7	11:00-15:00	120	11:00
	8	12:00-15:00	180	12:00
	9	14:00-17:00	300	14:00
	10	9:00-10:00	0	9:00
	11	9:00-14:00	0	9:00
	12	10:00-12:00	60	10:00
	13	9:00-15:00	0	9:00
Satellite 4	1	9:00-13:00	0	9:00
	2	11.30:16:00	150	11:30
	3	10:00-14:00	60	10:00
	4	12:00-17:00	180	12:00

	5	9:00-13:00	0	9:00
	6	10:00-16:00	60	10:00
	7	11:00-15:00	120	11:00
	8	12:00-15:00	180	12:00
	9	14:00-17:00	300	14:00
	10	10:00-11:00	60	10:00
	11	9:00-12:00	0	9:00
	12	13:00-14:00	240	13:00
	13	16:00-17:00	420	16:00
	14	10:30-14:00	90	10:30
	15	12:00-13:00	180	12:00
	16	9:00-10:30	0	9:00
Satellite 5	1	9:00-10:00	0	9:00
	2	12:00-13:00	180	12:00
	3	11:00-12:30	120	11:00
	4	14:00-15:00	300	14:00
	5	13:00-14:00	240	13:00
	6	16:00-17:00	420	16:00
	7	12:00-14:00	180	12:00
	8	11:00-15:00	120	11:00
	9	10:30-12:00	90	10:30
	10	9:00-11:00	0	9:00
	11	14:00-15:00	300	14:00
	12	12:00-13:30	180	12:00
Satellite 6	1	9:00-11:00	0	9:00
	2	12:00-13:00	180	12:00
	3	14:00-15:00	300	14:00
	4	15:00-16:00	360	15:00
	5	11:00-13:00	120	11:00
	6	13:00-15:00	240	13:00
	7	16:00-19:00	420	16:00
Satellite 7	1	10:00-12:00	60	10:00
	2	9:00-11:00	0	9:00
	3	9:00-13:00	0	9:00
	4	16:00-17:00	420	16:00
	5	9:00-12:00	0	9:00
	6	12:00-15:00	180	12:00
	7	12:00-13:00	180	12:00
	8	9:00-10:00	0	9:00
	9	9:00-10:30	0	9:00
	10	9:00-12:00	0	9:00
	11	12:00-13:00	180	12:00

	12	10:00-11:30	60	10:00
	13	13:00-16:00	240	13:00
	14	13:00-14:00	240	13:00
	15	9:00-11:30	60	10:00
	16	14:00-16:00	300	14:00
Satellite 8	1	11:00-12:30	120	11:00
	2	11:00-12:00	120	11:00
	3	17:00-18:00	480	17:00
	4	9:00-10:00	0	9:00
	5	16:00-17:00	420	16:00
	6	14:00-15:00	300	14:00
	7	13:00-14:30	240	13:00
	8	9:00-10:00	0	9:00
	9	12:00-14:00	180	12:00
	10	11:00-13:00	120	11:00
Satellite 9	1	11:00-12:30	120	11:00
	2	9:00-10:00	0	9:00
	3	17:00-18:00	480	17:00
	4	9:00-12:00	0	9:00
	5	15:00-16:00	360	15:00
	6	12:00-13:30	180	12:00
	7	10:00-11:00	60	10:00
	8	13:00-14:30	240	13:00
	9	10:00-12:00	60	10:00
	10	10:00-14:00	60	10:00
	11	15:00-16:00	360	15:00

The above table shows the delivery start time for every customer with consideration of the service time and the customer's preferred period. It has calculated the minutes from the starting delivery time of 9:00 am. These time windows are hard. This means the delivery should happen exactly within this period.

1.11 Experiment on Different Scenarios

1.11.1 Scenario 1: Increase the Vehicle Fleet Size in the Third Echelon Subject to the Constraints of the Case Study

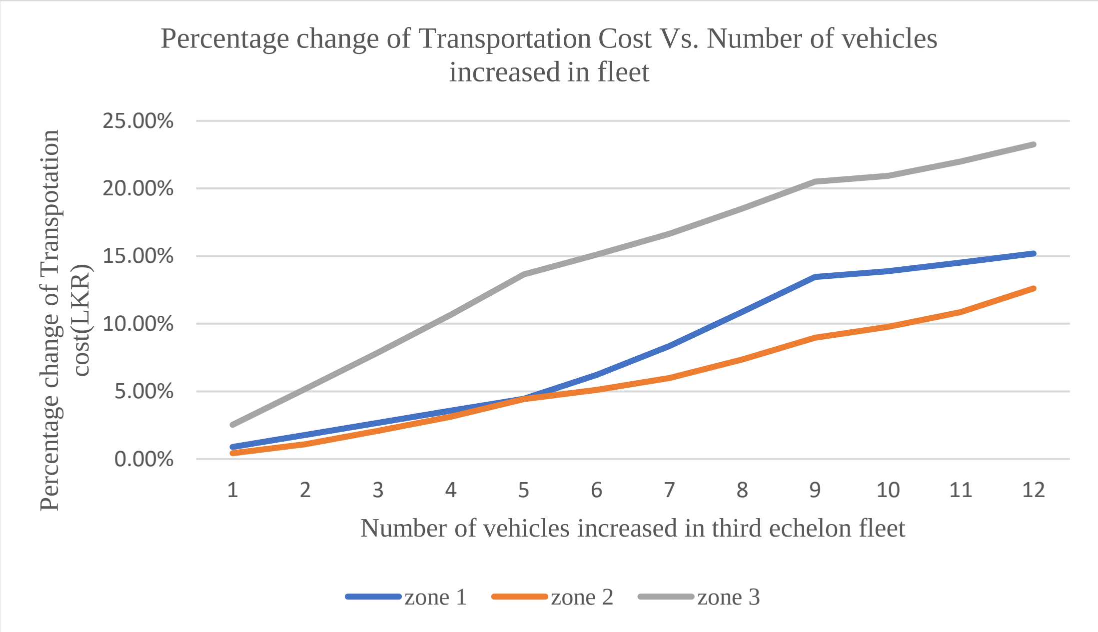


Figure 14: % change of transportation cos Vs. number of vehicles increased in fleet

Table 5: Transportation costs for the increase of vehicles

	Transportation costs (LKR)												
Number of vehicles increased	0	1	2	3	4	5	6	7	8	9	10	11	12
zone 1	56033.46	56533.46	57033.46	57533.45	58033.45	58533.46	59526.58	60713.36	62126.71	63570.09	63813.78	64173.63	64547.35
zone 2	56619.61	56863.3	57243.82	57797.9	58397.42	59129.62	59511.49	60011.49	60793.5	61691.97	62149.51	62774.52	63760.36

zone 3	72859.67	74703.8	76646.28	78600.97	80632.83	82812.82	83877.54	84984.96	86358.43	87801.81	88106.53	88878.29	89805.56

The data retrieved from the case study have been used to construct the scenarios. According to the given conditions, the number of customers served by the network has not changed and remained at 100. The cargo van fleet used in the third echelon of the network consists of a capacity of 200 kg in weight. Twelve vehicles are the maximum amount that can be added to the fleet of the third echelon without retrieving an infeasible solution. Therefore, regarding the case study, only a maximum of twelve cargo vans can be added to the third echelon fleet.

We have compared the percentage change of transportation costs compared to an initial case study to the increase in vehicle fleet in each zone. The transportation costs gradually increased with the addition of cargo vans to the fleet in every zone. The table has given the transportation costs incurred due to the increase in the vehicle fleet.

1.11.2 Scenario 2: Increase in the Number of Customers Served by the Vehicle Fleet

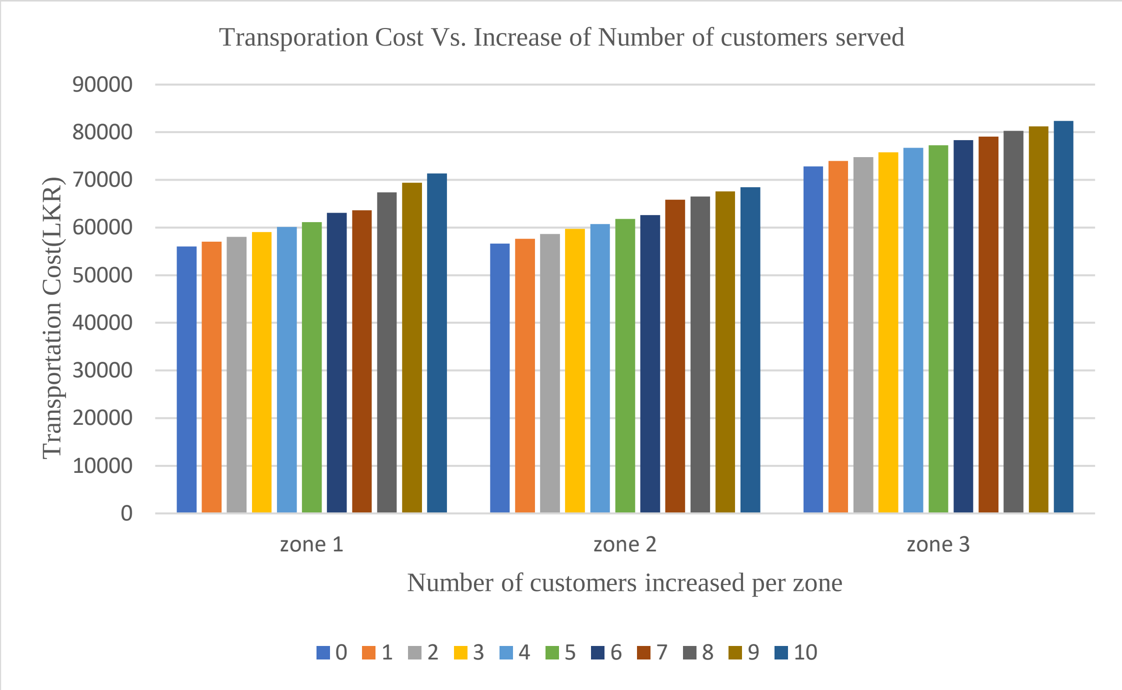


Figure 15: Transportation cost vs. increase of number of customers served

Table 6: Transportation costs for the added customers to the network

	Transportation cost (LKR)										
Number of added customers to the network	0	1	2	3	4	5	6	7	8	9	10
zone 1	56033.46	57033.73	58058.35	59058.36	60099.07	61105.21	63070.91	63630.2	67394.58	69423.58	71323.56
zone 2	56619.61	57663.14	58663.67	59715.6	60734.06	61825.32	62598.23	65832.12	66526.14	67568.25	68459.15
zone 3	72859.67	73953.38	74752.49	75754.2	76760.52	77272.18	78346.33	79060.38	80260.33	81261.49	82381.66

In scenario 2 we checked the feasibility of serving additional customers using the same fleet. We identified that we can only serve an additional 10 customers adhering to the capacity limitations of the vehicle fleets. We have followed the clustering procedure when increasing additional customers to the network. In each zone, the transportation costs have gradually increased when the fleet serves additional customers. Furthermore, the additional customers also should expect the delivery of their cargo within the service period.

1.11.3 Scenario 3: Increase of Customer's Time Window for Delivery of Freight

The time windows are subject to increase by hours. Further, the number of customers, demand quantities, and vehicle fleets have not changed. The considered time windows in the network are hard. In soft time windows, they are flexible to avoid or violate the time window at a cost. But in hard time windows, it is not allowed for a vehicle to serve a customer after the customer's most recent time to start the service. If the third echelon vehicle arrives at the customer before the customer's earliest service time then, they have to wait to begin service.

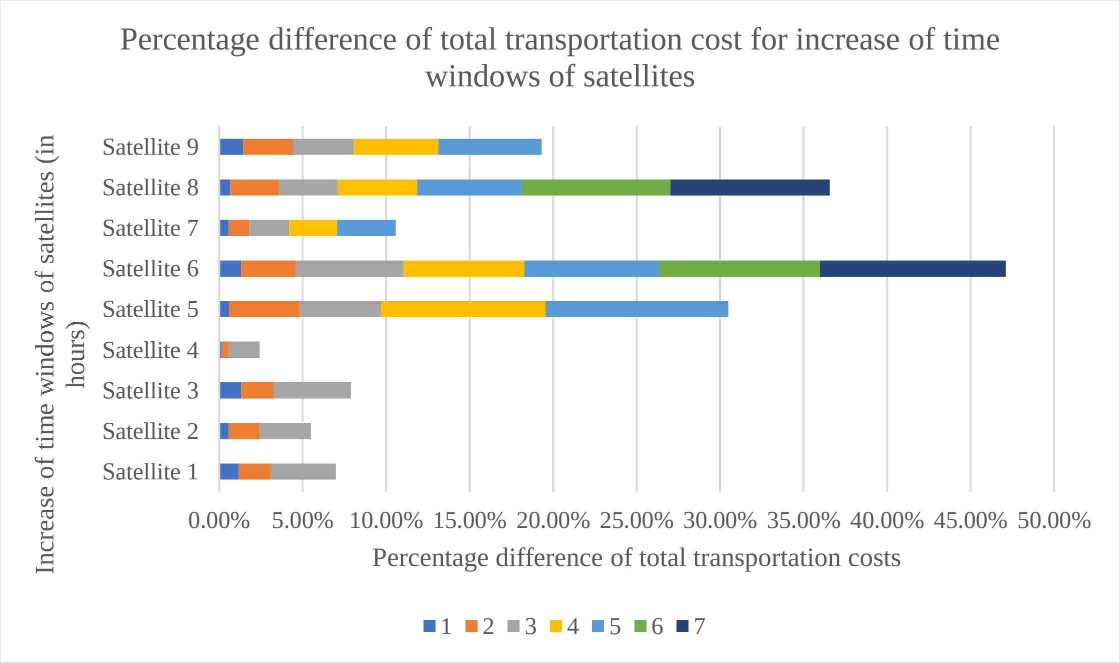


Figure 16: Percentage difference of total transportation cost for increase of time windows of satellites:

We analyzed the change in total transportation costs when the hard time windows are extended by the feasible amount of time. Here the hard time windows have been considered as the soft time window because of the extension of time to check up on the costs.

When the time window is exceeding the given delivery period of the fleet of vehicles, the solution was given as infeasible. In Satellite 1-4 all the customers can only extend their time window by another 4 hours to retrieve a feasible cost. Satellite 6 and satellite 8 can extend the time window up to another 7 hours. It is noticed that when the time window is extended by another 1hour or more, the total transportation cost also has gradually increased.

Chapter 4 has presented the quantitative research findings addressing the three research questions of this study. Chapter 5 summarizes the findings, conclusions, and suggestions for additional investigation.

CHAPTER FIVE: CONCLUSIONS

1.12 Results & Discussion

In this study, we introduced the 3E-VRP which deals with several satellites and examined the effectiveness of the use of satellites in an air freight distribution network. We elaborated the formulation for the common commodity situation, where the constraints do the flow synchronization.

we developed a mathematical model for three echelon air freight distribution networks to reduce the overall transportation cost. We discuss mixed integer linear programming formulations for this three-echelon capacitated vehicle routing problem with time windows (3E-CVRPTW) in the arc-based formulation. The connectivity between the three echelons has been made using demand as the connecting variable. The solved routes are presented in the graphs and obtained the total transportation costs for each zone. Further, the delivery starting times for each customer have been calculated considering the delivery time window and service time. The available fleet for each echelon is fully utilized to serve each facility and customer.

Finally, we have completed a scenario analysis of varying vehicle fleet sizes, the number of customers served, and time windows of delivery. The percentage change of transportation costs in all three zones is increasing when the number of vehicles increases in the third echelon fleet. In scenario 2 the transportation costs increase when the number of customers served is increased in all three zones. Also according to the case study, we can only increase the number of customers by another 10 and the solutions become infeasible when increasing further. In scenario 3 also the time windows of each customer respective to each satellite have increased and the percentage difference in total transportation costs has increased. Some future work can be done to improve our solution method and the proposed problem considering every detail from the experience obtained from the freight forwarder company.

1.13 Future Research Directions

In air cargo distribution fast and timely delivery is one of the important factors. Therefore, this research has opened a new path to develop the solution approaches for vehicle routing problems in a multi-echelon network associated with air freight distribution.

One of the main contributions of this research in the freight forwarder aspect is the mathematical formulation design of the distribution network which gives lower cost for real-life problem. The entire distribution network was designed to consider separately solving particular zones individually. This provided the advantage of easiness to solve the entire network when there is a large number of customers or satellites or depots involved. As future research direction, it can be suggested to develop the model to search for proper locations for satellites within different zones if the freight forwarding company is flexible to relocate their facilities. With the use of solution methods, the VRP can be solved to gain a total minimum transportation cost.

Furthermore, the model formulation can be further improved. There is a limitation we faced in the node-arc formulation. It is a large number of sub-tour elimination constraints. In future research, a new formulation can be developed for a real-life case study and can retrieve better solutions from exact methods. The proposed method can be developed by considering the large size of demand nodes or a large number of customers. Additionally, it can further improve with heterogeneous vehicle fleets and soft time windows.

1.14 Recommendations

Through this study, we believe that the solution methodology for a VRP in three echelon distribution networks has been clearly described. The developed three-echelon vehicle routing can be used to modify for a further number of echelons using the same constraints. Furthermore, it is suggested that solving the VRP with many nodes is easier with a clustering based heuristic approach. The clustering analysis can be used to form the network into groups and can solve them separately. The computation time is also less compared to other methods. Additionally, the homogeneous fleet of vehicles can be improved into a heterogeneous vehicle fleet and can solve using the clustering analysis at the initial stage of the study. Furthermore, scenario analysis is a robust way to find out the practicability of the solution approaches. And it gives the benefit of gaining better solutions in a practical manner than a theoretical aspect and is suitable for the real-life case study. The studied solution approach can be recommended for air freight distribution where it handles the relatively equal size of demand and a large customer base.

REFERENCES

Adulyasak, Y., & Jaillet, P. (2015). Models and Algorithms for Stochastic and Robust Vehicle Routing with Deadlines. *Https://Doi.Org/10.1287/Trsc.2014.0581*, *50*(2), 608–626. https://doi.org/10.1287/TRSC.2014.0581

Ahmadi-Javid, A., & Seddighi, A. H. (2013). A location-routing problem with disruption risk. *Transportation Research Part E: Logistics and Transportation Review*, *53*(1), 63–82. https://doi.org/10.1016/J.TRE.2013.02.002

Ahmadizar, F., Zeynivand, M., & Arkat, J. (2015). Two-level vehicle routing with cross-docking in a three-echelon supply chain: A genetic algorithm approach. *Applied Mathematical Modelling*, *39*(22), 7065–7081. https://doi.org/10.1016/J.APM.2015.03.005

Anderberg, M. R. (1973). *Análise de cluster para aplicativos*. 373.

Andres Figliozzi, M. (2012). The time dependent vehicle routing problem with time windows: Benchmark problems, an efficient solution algorithm, and solution characteristics. *Transportation Research Part E: Logistics and Transportation Review*, *48*(3), 616–636. https://doi.org/10.1016/J.TRE.2011.11.006

Arab, R., Ghaderi, S. F., & Tavakkoli-Moghaddam, R. (2018). Bi-objective inventory routing problem with backhauls under transportation risks: two meta-heuristics. *Https://Doi.Org/10.1080/19427867.2018.1533624*, *12*(2), 113–129. https://doi.org/10.1080/19427867.2018.1533624

Archetti, C., & Peirano, L. (2020). Air intermodal freight transportation: The freight forwarder service problem. *Omega (United Kingdom)*, *94*. https://doi.org/10.1016/J.OMEGA.2019.02.009

Archetti, C., Savelsbergh, M. W. P., & Grazia Speranza, M. (2008). To split or not to split: That is the question. *Transportation Research Part E: Logistics and Transportation Review*, *44*(1), 114–123. https://doi.org/10.1016/J.TRE.2006.04.003

Bae, H., & Moon, I. (2016). Multi-depot vehicle routing problem with time windows considering delivery and installation vehicles. *Applied Mathematical Modelling*, *40*(13–14), 6536–6549. https://doi.org/10.1016/J.APM.2016.01.059

Beheshtinia, M. A., Salmabadi, N., & Rahimi, S. (2021). A robust possibilistic programming model for production-routing problem in a three-echelon supply chain. *Journal of Modelling in Management*, *16*(4), 1328–1357. https://doi.org/10.1108/JM2-06-2020-0162

Beifert, A. (2016). Role of Air Cargo and Road Feeder Services for Regional Airports - Case Studies from the Baltic Sea Region. *Transport and Telecommunication*, *17*(2), 87–99. https://doi.org/10.1515/TTJ-2016-0008

Bektaş, T., & Laporte, G. (2011). The Pollution-Routing Problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250. https://doi.org/10.1016/J.TRB.2011.02.004

Bellmore, M., & Nemhauser, G. L. (1976). *The Traveling Salesman Problem: A Survey*. 443–448. https://doi.org/10.1007/978-3-642-51565-1_136

Beraldi, P., Bruni, M. E., Laganà, D., & Musmanno, R. (2015). The mixed capacitated general routing problem under uncertainty. *European Journal of Operational Research*, *240*(2), 382–392. https://doi.org/10.1016/J.EJOR.2014.07.023

Bertazzi, L., Coelho, L. C., de Maio, A., & Laganà, D. (2019). A matheuristic algorithm for the multi-depot inventory routing problem. *Transportation Research Part E: Logistics and Transportation Review*, *122*, 524–544. https://doi.org/10.1016/J.TRE.2019.01.005

Bezerra, S. N., de Souza, S. R., & Souza, M. J. F. (2018). A GVNS Algorithm for Solving the Multi-Depot Vehicle Routing Problem. *Electronic Notes in Discrete Mathematics*, *66*, 167–174. https://doi.org/10.1016/J.ENDM.2018.03.022

Blashfield, R. K., & Aldenderfer, M. S. (1988). The Methods and Problems of Cluster Analysis. *Handbook of Multivariate Experimental Psychology*, 447–473. https://doi.org/10.1007/978-1-4613-0893-5_14

Bodin, L. D. (1975). A taxonomic structure for vehicle routing and scheduling problems. *Computers and Urban Society*, *1*(1), 11–29. https://doi.org/10.1016/0305-7097(75)90003-4

Bombelli, A., Santos, B. F., & Tavasszy, L. (2020). Analysis of the air cargo transport network using a complex network theory perspective. *Transportation Research Part E: Logistics and Transportation Review*, *138*, 101959. https://doi.org/10.1016/J.TRE.2020.101959

Brandão de Oliveira, H. C., & Vasconcelos, G. C. (2010). A hybrid search method for the vehicle routing problem with time windows. *Annals of Operations Research*, *180*(1), 125–144. https://doi.org/10.1007/S10479-008-0487-Y

BrandãO, J. C. S., & Mercer, A. (2017). The multi-trip vehicle routing problem. *Https://Doi.Org/10.1057/Palgrave.Jors.2600595*, *49*(8), 799–805. https://doi.org/10.1057/PALGRAVE.JORS.2600595

Bulhões, T., Sadykov, R., & Uchoa, E. (2018). A branch-and-price algorithm for the Minimum Latency Problem. *Computers & Operations Research*, *93*, 66–78. https://doi.org/10.1016/J.COR.2018.01.016

Caceres-Cruz, J., Arias, P., Guimarans, D., Riera, D., & Juan, A. A. (2014). Rich Vehicle Routing Problem. *ACM Computing Surveys (CSUR)*, *47*(2). https://doi.org/10.1145/2666003

Chang, M. S. (2011). A vehicle routing problem with time windows and stochastic demands. *Http://Dx.Doi.Org/10.1080/02533839.2005.9671048*, *28*(5), 783–794. https://doi.org/10.1080/02533839.2005.9671048

Chang, P. Y., Chen, K., & Lin, H. Y. (2010). Determining optimal convenient store location in logistics network with consideration of transshipment cost. *40th International Conference on Computers and Industrial Engineering: Soft Computing Techniques for Advanced Manufacturing and Service Systems, CIE40 2010*. https://doi.org/10.1109/ICCIE.2010.5668202

Chen, L., Hà, M. H., Langevin, A., & Gendreau, M. (2014). Optimizing road network daily maintenance operations with stochastic service and travel times. *Transportation Research Part E: Logistics and Transportation Review*, *64*, 88–102. https://doi.org/10.1016/J.TRE.2014.02.002

Cheung, R. K., & Hang, D. D. (2010). Multi-attribute label matching algorithms for vehicle routing problems with time windows and backhauls. *Http://Dx.Doi.Org/10.1080/07408170304371*, *35*(3), 191–205. https://doi.org/10.1080/07408170304371

Christiansen, C. H., & Lysgaard, J. (2007). A branch-and-price algorithm for the capacitated vehicle routing problem with stochastic demands. *Operations Research Letters*, *35*(6), 773–781. https://doi.org/10.1016/J.ORL.2006.12.009

Clarke, G., & Wright, J. W. (1964a). Scheduling of Vehicles from a Central Depot to a Number of Delivery Points. *Operations Research*, *12*(4), 568–581. https://doi.org/10.1287/OPRE.12.4.568

Clarke, G., & Wright, J. W. (1964b). Scheduling of Vehicles from a Central Depot to a Number of Delivery Points. *Https://Doi.Org/10.1287/Opre.12.4.568*, *12*(4), 568–581. https://doi.org/10.1287/OPRE.12.4.568

Coene, S., Arnout, A., & Spieksma, F. C. R. (2017). On a periodic vehicle routing problem. *Https://Doi.Org/10.1057/Jors.2009.154*, *61*(12), 1719–1728. https://doi.org/10.1057/JORS.2009.154

Cohen, A. P., Shaheen, S. A., & Farrar, E. M. (2021). Urban Air Mobility: History, Ecosystem, Market Potential, and Challenges. *IEEE Transactions on Intelligent Transportation Systems*, *22*(9), 6074–6087. https://doi.org/10.1109/TITS.2021.3082767

Crainic, T. G., Perboli, G., Mancini, S., & Tadei, R. (2010). Two-Echelon Vehicle Routing Problem: A satellite location analysis. *Procedia - Social and Behavioral Sciences*, *2*(3), 5944–5955. https://doi.org/10.1016/J.SBSPRO.2010.04.009

Crevier, B., Cordeau, J. F., & Laporte, G. (2007). The multi-depot vehicle routing problem with inter-depot routes. *European Journal of Operational Research*, *176*(2), 756–773. https://doi.org/10.1016/J.EJOR.2005.08.015

Cullen, F. H., Jarvis, J. J., & Ratliff, H. D. (1981). Set partitioning based heuristics for interactive routing. *Networks*, *11*(2), 125–143. https://doi.org/10.1002/NET.3230110206

Dantzig, G. B., & Ramser, J. H. (1959a). The Truck Dispatching Problem. *Management Science*, *6*(1), 80–91. https://doi.org/10.1287/MNSC.6.1.80

Dantzig, G. B., & Ramser, J. H. (1959b). The Truck Dispatching Problem. *Http://Dx.Doi.Org/10.1287/Mnsc.6.1.80*, *6*(1), 80–91. https://doi.org/10.1287/MNSC.6.1.80

Debbage, K., & Debbage, N. (2021). Air Freight Logistics. *International Encyclopedia of Transportation*, 361–368. https://doi.org/10.1016/B978-0-08-102671-7.10270-2

Demir, A. S. (2022). Modeling and forecasting of CO2 emissions resulting from air transport with genetic algorithms: the United Kingdom case. *Theoretical and Applied Climatology*, *150*(1), 777–785. https://doi.org/10.1007/S00704-022-04203-4/FIGURES/9

Derigs, U., Kurowsky, R., & Vogel, U. (2011). Solving a real-world vehicle routing problem with multiple use of tractors and trailers and EU-regulations for drivers arising in air cargo road feeder services. *European Journal of Operational Research*, *213*(1), 309–319. https://doi.org/10.1016/J.EJOR.2011.03.032

Derigs, U., & Reuter, K. (2017). A simple and efficient tabu search heuristic for solving the open vehicle routing problem. *Https://Doi.Org/10.1057/Jors.2008.107*, *60*(12), 1658–1669. https://doi.org/10.1057/JORS.2008.107

Desrochers, M., Desrosiers, J., & Solomon, M. (1992). A New Optimization Algorithm for the Vehicle Routing Problem with Time Windows.

Https://Doi.Org/10.1287/Opre.40.2.342, *40*(2), 342–354. https://doi.org/10.1287/OPRE.40.2.342

Drexl, M., & Schneider, M. (2015). A survey of variants and extensions of the location-routing problem. *European Journal of Operational Research*, *241*(2), 283–308. https://doi.org/10.1016/J.EJOR.2014.08.030

Dursun, Ö. O., & Özger, A. (2022). Multi-depot heterogeneous fleet vehicle routing problem with time windows: Airline and roadway integrated routing. *International Journal of Industrial Engineering Computations*, *13*(3), 435–456. https://doi.org/10.5267/J.IJIEC.2022.1.001

el Hassani, A. H., Bouhafs, L., & Koukam, A. (2008). A Hybrid Ant Colony System Approach for the Capacitated Vehicle Routing Problem and the Capacitated Vehicle Routing Problem with Time Windows. *Vehicle Routing Problem*. https://doi.org/10.5772/5640

Elalouf, A., Tsadikovich, D., & Hovav, S. (2021). A simulation-based approach for improving the clinical blood sample supply chain. *Health Care Management Science*, *24*(1), 216–233. https://doi.org/10.1007/S10729-020-09534-0

Errico, F., Desaulniers, G., Gendreau, M., Rei, W., & Rousseau, L. M. (2016). A priori optimization with recourse for the vehicle routing problem with hard time windows and stochastic service times. *European Journal of Operational Research*, *249*(1), 55–66. https://doi.org/10.1016/J.EJOR.2015.07.027

Fang, Z., & Mao, J. (2020). Energy-Efficient Elevating Transfer Vehicle Routing for Automated Multi-Level Material Handling Systems. *IEEE Transactions on Automation Science and Engineering*, *17*(3), 1107–1123. https://doi.org/10.1109/TASE.2019.2921631

Feillet, D., Garaix, T., Lehuédé, F., Péton, O., & Quadri, D. (2014). A new consistent vehicle routing problem for the transportation of people with disabilities. *Networks*, *63*(3), 211–224. https://doi.org/10.1002/NET.21538

Fu, C. H. (2013). Combined optimization of fixed-partition and integral-ratio horizon policy for the three-echelon inventory routing problem. *Journal of Applied Sciences*, *13*(12), 2239–2245. https://doi.org/10.3923/JAS.2013.2239-2245

Gardiner, J., & Ison, S. (2007). *Literature Review on air freight growth Client: Sustainable Development Commission*.

Gelhausen, M. C., Berster, P., & Wilken, D. (2013). Do airport capacity constraints have a serious impact on the future development of air traffic? *Journal of Air Transport Management*, *28*, 3–13. https://doi.org/10.1016/J.JAIRTRAMAN.2012.12.004

Gendreau, M., & Rei, W. (2007). *Local branching cuts for the 0-1 integer L-Shaped algorithm*. https://www.academia.edu/16736364/Local_branching_cuts_for_the_0_1_integer_L_Shaped_algorithm

Giallanza, A., & Puma, G. L. (2020). Fuzzy green vehicle routing problem for designing a three echelons supply chain. *Journal of Cleaner Production*, *259*. https://doi.org/10.1016/J.JCLEPRO.2020.120774

Goetschalckx, M., & Jacobs-Blecha, C. (1989). The vehicle routing problem with backhauls. *European Journal of Operational Research*, *42*(1), 39–51. https://doi.org/10.1016/0377-2217(89)90057-X

Gounaris, C. E., Wiesemann, W., & Floudas, C. A. (2013). The Robust Capacitated Vehicle Routing Problem Under Demand Uncertainty. *Https://Doi.Org/10.1287/Opre.1120.1136*, *61*(3), 677–693. https://doi.org/10.1287/OPRE.1120.1136

Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L. M. (2016). An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. *European Journal of Operational Research*, *254*(1), 80–91. https://doi.org/10.1016/J.EJOR.2016.03.040

Gromicho, J., van Hoorn, J. J., Kok, A. L., & Schutten, J. M. J. (2012). Restricted dynamic programming: A flexible framework for solving realistic VRPs. *Computers & Operations Research*, *39*(5), 902–909. https://doi.org/10.1016/J.COR.2011.07.002

Guastaroba, G., Speranza, M. G., & Vigo, D. (2016). Intermediate facilities in freight transportation planning: A survey. *Transportation Science*, *50*(3), 763–789. https://doi.org/10.1287/TRSC.2015.0631

Guastaroba, G., Speranza, M. G., Vigo, D., Guastaroba, G., Speranza, M. G., & Vigo, D. (2016). Intermediate Facilities in Freight Transportation Planning: A Survey. *Transportation Science*, *50*(3), 763–789. https://doi.org/10.1287/TRSC.2015.0631

Häckel, S., & Dippold, P. (2009). The Bee Colony-inspired Algorithm (BCiA): A two-stage approach for solving the vehicle routing problem with time windows. *Proceedings of the 11th Annual Genetic and Evolutionary Computation Conference, GECCO-2009*, 25–32. https://doi.org/10.1145/1569901.1569906

Hashemi, L., Mahmoodi, A., Jasemi, M., Millar, R. C., & Laliberté, J. (2022). Designing a locating-routing three-echelon supply chain network under uncertainty. *International Journal of Intelligent Computing and Cybernetics*. https://doi.org/10.1108/IJICC-08-2021-0163

Haugland, D., Ho, S. C., & Laporte, G. (2007). Designing delivery districts for the vehicle routing problem with stochastic demands. *European Journal of Operational Research*, *180*(3), 997–1010. https://doi.org/10.1016/J.EJOR.2005.11.070

Ho, W., Ho, G. T. S., Ji, P., & Lau, H. C. W. (2008). A hybrid genetic algorithm for the multi-depot vehicle routing problem. *Engineering Applications of Artificial Intelligence*, *21*, 548–557. https://doi.org/10.1016/j.engappai.2007.06.001

Hsu, C. I., Hung, S. F., & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of Food Engineering*, *80*(2), 465–475. https://doi.org/10.1016/J.JFOODENG.2006.05.029

Hu, W., Mao, J., & Wei, K. (2017). Energy-efficient rail guided vehicle routing for two-sided loading/unloading automated freight handling system. *European Journal of Operational Research*, *258*(3), 943–957. https://doi.org/10.1016/J.EJOR.2016.09.001

Huang, K., Lu, C., & Lian, M. (2018). Research on modeling and algorithm for three-echelon location-routing problem. *Xitong Gongcheng Lilun Yu Shijian/System Engineering Theory and Practice*, *38*(3), 743–754. https://doi.org/10.12011/1000-6788(2018)03-0743-12

Imran, A., Salhi, S., & Wassan, N. A. (2009). A variable neighborhood-based heuristic for the heterogeneous fleet vehicle routing problem. *European Journal of Operational Research*, *197*(2), 509–518. https://doi.org/10.1016/J.EJOR.2008.07.022

Jabali, O., Rei, W., Gendreau, M., & Laporte, G. (2014). Partial-route inequalities for the multi-vehicle routing problem with stochastic demands. *Discrete Applied Mathematics*, *177*, 121–136. https://doi.org/10.1016/J.DAM.2014.05.040

Kaboudani, Y., Ghodsypour, S. H., Kia, H., & Shahmardan, A. (2020). Vehicle routing and scheduling in cross docks with forward and reverse logistics. *Operational Research*, *20*(3), 1589–1622. https://doi.org/10.1007/S12351-018-0396-Z

Kchaou Boujelben, M., Gicquel, C., & Minoux, M. (2014). A distribution network design problem in the automotive industry: MIP formulation and heuristics. *Computers & Operations Research*, *52*(PART A), 16–28. https://doi.org/10.1016/J.COR.2014.07.007

Kchaou-Beljeben, M., Gicquel, C., & Minoux, M. (n.d.). *A distribution network design problem in the automotive industry: MIP formulation and heuristics*.

Kenyon, A. S., & Morton, D. P. (2003). Stochastic Vehicle Routing with Random Travel Times. *Https://Doi.Org/10.1287/Trsc.37.1.69.12820*, *37*(1), 69–82. https://doi.org/10.1287/TRSC.37.1.69.12820

Khan, N., Hassan, A. U., Fahad, S., & Naushad, M. (2020). Factors Affecting Tourism Industry and Its Impacts on Global Economy of the World. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3559353

Kim, G., Ong, Y. S., Heng, C. K., Tan, P. S., & Zhang, N. A. (2015). City Vehicle Routing Problem (City VRP): A Review. *Undefined*, *16*(4), 1654–1666. https://doi.org/10.1109/TITS.2015.2395536

Knight, K. W., & Hofer, J. P. (1968). Vehicle Scheduling with Timed and Connected Calls: A Case Study. *Journal of the Operational Research Society 1968 19:3*, *19*(3), 299–310. https://doi.org/10.1057/JORS.1968.73

Konstantakopoulos, G. D., Gayialis, S. P., Kechagias, E. P., Papadopoulos, G. A., & Tatsiopoulos, I. P. (2021). An algorithmic approach for sustainable and collaborative logistics: A case study in Greece. *International Journal of Information Management Data Insights*, *1*(1), 100010. https://doi.org/10.1016/J.JJIMEI.2021.100010

Kritikos, M. N., & Ioannou, G. (2010). The balanced cargo vehicle routing problem with time windows. *International Journal of Production Economics*, *123*(1), 42–51. https://doi.org/10.1016/J.IJPE.2009.07.006

Labadie, Nacima. (2015). *Metaheuristics for vehicle routing problems*. https://www.wiley.com/en-us/Metaheuristics+for+Vehicle+Routing+Problems-p-9781119136781

Lahyani, R., Khemakhem, M., & Semet, F. (2015). Rich vehicle routing problems: From a taxonomy to a definition. *European Journal of Operational Research*, *241*(1), 1–14. https://doi.org/10.1016/J.EJOR.2014.07.048

Laporte, G., Louveaux, F. v., & van Hamme, L. (2002a). An Integer L-Shaped Algorithm for the Capacitated Vehicle Routing Problem with Stochastic Demands. *Https://Doi.Org/10.1287/Opre.50.3.415.7751*, *50*(3), 415–423. https://doi.org/10.1287/OPRE.50.3.415.7751

Laporte, G., Louveaux, F. v., & van Hamme, L. (2002b). An Integer L-Shaped Algorithm for the Capacitated Vehicle Routing Problem with Stochastic Demands. *Https://Doi.Org/10.1287/Opre.50.3.415.7751*, *50*(3), 415–423. https://doi.org/10.1287/OPRE.50.3.415.7751

Laporte, G., Musmanno, R., & Vocaturo, F. (2009). An Adaptive Large Neighbourhood Search Heuristic for the Capacitated Arc-Routing Problem with Stochastic Demands. *Https://Doi.Org/10.1287/Trsc.1090.0290*, *44*(1), 125–135. https://doi.org/10.1287/TRSC.1090.0290

Laporte, G., Nobert, Y., & Taillefer, S. (1988). Solving a Family of Multi-Depot Vehicle Routing and Location-Routing Problems. *Https://Doi.Org/10.1287/Trsc.22.3.161*, *22*(3), 161–172. https://doi.org/10.1287/TRSC.22.3.161

Lefever, W., Aghezzaf, E. H., Hadj-Hamou, K., & Penz, B. (2018). Analysis of an improved branch-and-cut formulation for the Inventory-Routing Problem with Transshipment. *Computers & Operations Research*, *98*, 137–148. https://doi.org/10.1016/J.COR.2018.05.023

Lei, H., Laporte, G., & Guo, B. (2011a). A generalized variable neighborhood search heuristic for the capacitated vehicle routing problem with stochastic service times. *TOP 2011 20:1*, *20*(1), 99–118. https://doi.org/10.1007/S11750-011-0188-6

Lei, H., Laporte, G., & Guo, B. (2011b). The capacitated vehicle routing problem with stochastic demands and time windows. *Computers & Operations Research*, *38*(12), 1775–1783. https://doi.org/10.1016/J.COR.2011.02.007

Li, H., Bai, M., Wang, H., & Jian, X. (2019). The Truck Routing and Aircraft Assignment Problem with Time Windows. *CICTP 2019: Transportation in China - Connecting the World - Proceedings of the 19th COTA International Conference of Transportation Professionals*, 4575–4587. https://doi.org/10.1061/9780784482292.395

Li, J., Wang, R., Li, T., Lu, Z., & Pardalos, P. M. (2018). Benefit analysis of shared depot resources for multi-depot vehicle routing problem with fuel consumption. *Transportation Research Part D: Transport and Environment*, *59*, 417–432. https://doi.org/10.1016/j.trd.2018.01.026

Lin, C., Choy, K. L., Ho, G. T. S., Chung, S. H., & Lam, H. Y. (2014). Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Systems with Applications*, *41*(4), 1118–1138. https://doi.org/10.1016/J.ESWA.2013.07.107

Lin, C. K. Y., & Kwok, R. C. W. (2006). Multi-objective metaheuristics for a location-routing problem with multiple use of vehicles on real data and simulated data. *European Journal of Operational Research*, *175*(3), 1833–1849. https://doi.org/10.1016/J.EJOR.2004.10.032

Lin, S. W., Yu, V. F., & Chou, S. Y. (2010). A note on the truck and trailer routing problem. *Expert Systems with Applications*, *37*(1), 899–903. https://doi.org/10.1016/J.ESWA.2009.06.077

Luiz Usberti, F., Morelato França, P., & França, A. L. M. (2013). GRASP with evolutionary path-relinking for the capacitated arc routing problem. *Computers & Operations Research*, *40*(12), 3206–3217. https://doi.org/10.1016/J.COR.2011.10.014

Madsen, O. B. G. (1983). Methods for solving combined two level location-routing problems of realistic dimensions. *European Journal of Operational Research*, *12*(3), 295–301. https://doi.org/10.1016/0377-2217(83)90199-6

Mancini, S. (2017). The Hybrid Vehicle Routing Problem. *Transportation Research Part C: Emerging Technologies*, *78*, 1–12. https://doi.org/10.1016/J.TRC.2017.02.004

Meliani, Y., Elhaq, S. L., Hani, Y., & Mhamedi, A. el. (2019). Tabu Search for urban freight VRP: Fundamental aspects and parameters tuning evaluation. *International Colloquium on Logistics and Supply Chain Management, LOGISTIQUA 2019*. https://doi.org/10.1109/LOGISTIQUA.2019.8907263

Melnyk, M. v., & Мельник, M. B. (2020). *Organization of sale of logistics operator services*. https://er.nau.edu.ua/handle/NAU/49872

Memedovic, O., Ojala, L., Rodrigue, J. P., & Naula, T. (2008). Fuelling the global value chains: what role for logistics capabilities? *International Journal of Technological Learning, Innovation and Development*, *1*(3), 353–374. https://doi.org/10.1504/IJTLID.2008.019978

Min, H. (1989). THE MULTIPLE VEHICLE ROUTING PROBLEM WITH SIMULTANEOUS DELIVERY AND PICK-UP POINTS. *Transportation Research Part A: Policy and Practice*, *23A*(5).

Montané, F. A. T., & Galvão, R. D. (2006). A tabu search algorithm for the vehicle routing problem with simultaneous pick-up and delivery service. *Computers & Operations Research*, *33*(3), 595–619. https://doi.org/10.1016/J.COR.2004.07.009

Mousavi, S. M., Tavakkoli-Moghaddam, R., & Jolai, F. (2013). A possibilistic programming approach for the location problem of multiple cross-docks and vehicle routing scheduling under uncertainty. *Engineering Optimization*, *45*(10), 1223–1249. https://doi.org/10.1080/0305215X.2012.729053

Nadizadeh, A., & Hosseini Nasab, H. (2014). Solving the dynamic capacitated location-routing problem with fuzzy demands by hybrid heuristic algorithm. *European Journal of Operational Research*, *238*(2), 458–470. https://doi.org/10.1016/J.EJOR.2014.04.012

Nguyen, H. van, & Phung, P. P. (2021). Adaptive inertia weight particle swarm optimisation for a multi-objective capacitated vehicle routing problem with time window in air freight forwarding. *International Journal of Logistics Systems and Management*, *40*(3), 423–442. https://doi.org/10.1504/ijlsm.2021.120251

Nikfarjam, A., & Moosavi, A. (2021). An integrated (1, T) inventory policy and vehicle routing problem under uncertainty: an accelerated Benders decomposition algorithm. *Transportation Letters*, *13*(2), 104–124. https://doi.org/10.1080/19427867.2020.1714843

Panova, Y., Hilletofth, P., Panova, A., & Hongsheng, X. (2020). Application of the Just-In-Time Approach to a Third-Generation Port. *Operations and Supply Chain Management: An International Journal*, *13*(3), 279–293. https://doi.org/10.31387/OSCM0420269

Penna, P. H. V., Subramanian, A., Ochi, L. S., Vidal, T., & Prins, C. (2018). A Hybrid Heuristic for a Broad Class of Vehicle Routing Problems with Heterogeneous Fleet. *Annals of Operations Research*, *273*(1–2), 5–74. https://doi.org/10.1007/s1047

Peres, I. T., Repolho, H. M., Martinelli, R., & Monteiro, N. J. (2017). Optimization in inventory-routing problem with planned transshipment: A case study in the retail industry. *International Journal of Production Economics*, *193*, 748–756. https://doi.org/10.1016/J.IJPE.2017.09.002

Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, *225*(1), 1–11. https://doi.org/10.1016/J.EJOR.2012.08.015

Qiu, Y., Qiao, J., & Pardalos, P. M. (2019). Optimal production, replenishment, delivery, routing and inventory management policies for products with perishable inventory. *Omega*, *82*, 193–204. https://doi.org/10.1016/J.OMEGA.2018.01.006

Quak, H. J., & de Koster, M. B. M. (2008). Delivering Goods in Urban Areas: How to Deal with Urban Policy Restrictions and the Environment. *Https://Doi.Org/10.1287/Trsc.1080.0235*, *43*(2), 211–227. https://doi.org/10.1287/TRSC.1080.0235

Qureshi, A. G., Taniguchi, E., & Yamada, T. (2010). Exact solution for the vehicle routing problem with semi soft time windows and its application. *Procedia - Social and Behavioral Sciences*, *2*(3), 5931–5943. https://doi.org/10.1016/J.SBSPRO.2010.04.008

Rabbouch, B., Saâdaoui, F., & Mraihi, R. (2021). Efficient implementation of the genetic algorithm to solve rich vehicle routing problems. *Operational Research*, *21*(3), 1763–1791. https://doi.org/10.1007/S12351-019-00521-0/TABLES/12

Razmi Rad, S., Farah, H., Taale, H., van Arem, B., & Hoogendoorn, S. P. (2021). The impact of a dedicated lane for connected and automated vehicles on the behaviour of drivers of manual vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, *82*, 141–153. https://doi.org/10.1016/J.TRF.2021.08.010

Renaud, J., & Boctor, F. F. (2002). A sweep-based algorithm for the fleet size and mix vehicle routing problem. *European Journal of Operational Research*, *140*(3), 618–628. https://doi.org/10.1016/S0377-2217(01)00237-5

Repoussis, P. P., & Tarantilis, C. D. (2010). Solving the Fleet Size and Mix Vehicle Routing Problem with Time Windows via Adaptive Memory Programming. *Transportation Research Part C: Emerging Technologies*, *18*(5), 695–712. https://doi.org/10.1016/J.TRC.2009.08.004

Sales, M. (2016). A brief history of the air freight industry. *Air Cargo Management*, 46–64. https://doi.org/10.4324/9781315620169-14

Salhi, S., Imran, A., & Wassan, N. A. (2014). The multi-depot vehicle routing problem with heterogeneous vehicle fleet: Formulation and a variable neighborhood search implementation. *Computers & Operations Research*, *52*, 315–325. https://doi.org/10.1016/J.COR.2013.05.011

Sanghatawatana, P., Pornchaiwiseskul, P., & Lohatepanont, M. (2019). Redesign of three-echelon multi-commodity distribution network. *Engineering Journal*, *23*(1), 49–74. https://doi.org/10.4186/EJ.2019.23.1.49

Saragih, N. I., Bahagia, S. N., Suprayogi, & Syabri, I. (2019). A heuristic method for location-inventory-routing problem in a three-echelon supply chain system. *Computers and Industrial Engineering*, *127*, 875–886. https://doi.org/10.1016/J.CIE.2018.11.026

Savelsbergh, M. W. P. (1985). Local search in routing problems with time windows. *Annals of Operations Research 1985 4:1*, *4*(1), 285–305. https://doi.org/10.1007/BF02022044

Secomandi, N., & Margot, F. (2008). Reoptimization Approaches for the Vehicle-Routing Problem with Stochastic Demands. *Https://Doi.Org/10.1287/Opre.1080.0520*, *57*(1), 214–230. https://doi.org/10.1287/OPRE.1080.0520

Silva, M. M., Subramanian, A., & Ochi, L. S. (2015). An iterated local search heuristic for the split delivery vehicle routing problem. *Computers & Operations Research*, *53*, 234–249. https://doi.org/10.1016/J.COR.2014.08.005

Sitek, P., & Stefanski, T. (2017). Modeling and optimization of multi-echelon transportation systems-A hybrid approach. *Proceedings of the 2017 Federated Conference on Computer Science and Information Systems, FedCSIS 2017*, 1057–1064. https://doi.org/10.15439/2017F80

Sluijk, N., Florio, A. M., Kinable, J., Dellaert, N., & van Woensel, T. (2022). Two-echelon vehicle routing problems: A literature review. *European Journal of Operational Research*. https://doi.org/10.1016/J.EJOR.2022.02.022

Solomon, M. M. (1987). Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints. *Https://Doi.Org/10.1287/Opre.35.2.254*, *35*(2), 254–265. https://doi.org/10.1287/OPRE.35.2.254

Soysal, M., & Çimen, M. (2017). A Simulation Based Restricted Dynamic Programming approach for the Green Time Dependent Vehicle Routing Problem. *Computers & Operations Research*, *88*, 297–305. https://doi.org/10.1016/J.COR.2017.06.023

Srivastava, R. (1993). Alternate solution procedures for the location-routing problem. *Omega*, *21*(4), 497–506. https://doi.org/10.1016/0305-0483(93)90082-V

Stiller, H. (2003). The Effect of e-Commerce on Transportation Demand. *Making Urban Transport Sustainable*, 67–83. https://doi.org/10.1057/9780230523838_4

Tang, J., Pan, Z., Fung, R. Y. K., & Lau, H. (2009). Vehicle routing problem with fuzzy time windows. *Fuzzy Sets and Systems*, *160*(5), 683–695. https://doi.org/10.1016/J.FSS.2008.09.016

Taniguchi, E., & Shimamoto, H. (2004). Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. *Transportation Research Part C: Emerging Technologies*, *12*(3–4), 235–250. https://doi.org/10.1016/J.TRC.2004.07.007

Taş, D., Dellaert, N., van Woensel, T., & de Kok, T. (2013). Vehicle routing problem with stochastic travel times including soft time windows and service costs. *Computers & Operations Research*, *40*(1), 214–224. https://doi.org/10.1016/J.COR.2012.06.008

Toth, P., Vigo, D., & Society for Industrial and Applied Mathematics. (n.d.-a). *Vehicle routing : problems, methods, and applications*. 463.

Toth, P., Vigo, D., & Society for Industrial and Applied Mathematics. (n.d.-b). *Vehicle routing : problems, methods, and applications*. 463. Retrieved September 28, 2022, from https://books.google.com/books/about/Vehicle_Routing.html?id=YL_CswEACAAJ

Validi, S., Bhattacharya, A., & Byrne, P. J. (2021). An evaluation of three DoE-guided meta-heuristic-based solution methods for a three-echelon sustainable distribution network. *Annals of Operations Research*, *296*(1–2), 421–469. https://doi.org/10.1007/S10479-020-03746-X

Wang, Y., Ma, X., Li, Z., Liu, Y., Xu, M., & Wang, Y. (2017). Profit distribution in collaborative multiple centers vehicle routing problem. *Journal of Cleaner Production*, *144*, 203–219. https://doi.org/10.1016/J.JCLEPRO.2017.01.001

Wang, Y., Zhang, S., Guan, X., Peng, S., Wang, H., Liu, Y., & Xu, M. (2020). Collaborative multi-depot logistics network design with time window assignment. *Expert Systems with Applications*, *140*. https://doi.org/10.1016/J.ESWA.2019.112910

Xia, Y., Fu, Z., Pan, L., & Duan, F. (2018). Tabu search algorithm for the distance-constrained vehicle routing problem with split deliveries by order. *PLOS ONE*, *13*(5), e0195457. https://doi.org/10.1371/JOURNAL.PONE.0195457

Xu, Y., Wang, L., & Yang, Y. (2012). A New Variable Neighborhood Search Algorithm for the Multi Depot Heterogeneous Vehicle Routing Problem with Time Windows. *Electronic Notes in Discrete Mathematics*, *39*, 289–296. https://doi.org/10.1016/J.ENDM.2012.10.038

Yadollahi, E., Aghezzaf, E. H., Walraevens, J., Raa, B., & Claeys, D. (2019). Evaluating approximate solution models for the stochastic periodic inventory routing problem. *Journal of Manufacturing Systems*, *50*, 25–35. https://doi.org/10.1016/J.JMSY.2018.11.001

Yang, W. H., Mathur, K., & Ballou, R. H. (2000). Stochastic Vehicle Routing Problem with Restocking. *Https://Doi.Org/10.1287/Trsc.34.1.99.12278*, *34*(1), 99–112. https://doi.org/10.1287/TRSC.34.1.99.12278

Yu, B., & Yang, Z. Z. (2011). An ant colony optimization model: The period vehicle routing problem with time windows. *Transportation Research Part E: Logistics and Transportation Review*, *47*(2), 166–181. https://doi.org/10.1016/J.TRE.2010.09.010

Yu, G., & Yang, Y. (2017). Dynamic routing with real-time traffic information. *Operational Research 2017 19:4*, *19*(4), 1033–1058. https://doi.org/10.1007/S12351-017-0314-9

Yücenur, G. N., & Demirel, N. Ç. (2011). A new geometric shape-based genetic clustering algorithm for the multi-depot vehicle routing problem. *Expert Systems with Applications*, *38*(9), 11859–11865. https://doi.org/10.1016/J.ESWA.2011.03.077

Zachariadis, E. E., & Kiranoudis, C. T. (2010). An open vehicle routing problem metaheuristic for examining wide solution neighborhoods. *Computers & Operations Research*, *37*(4), 712–723. https://doi.org/10.1016/J.COR.2009.06.021

Zachariadis, E. E., Tarantilis, C. D., & Kiranoudis, C. T. (2016). The Vehicle Routing Problem with Simultaneous Pick-ups and Deliveries and Two-Dimensional

Loading Constraints. *European Journal of Operational Research*, *251*(2), 369–386. https://doi.org/10.1016/j.ejor.2015.11.018

Zakharov, V. v., & Shirokikh, V. A. (2018). Heuristic evaluation of the characteristic function in the Cooperative Inventory Routing Game. *Journal on Vehicle Routing Algorithms*, *1*(1), 19–32. https://doi.org/10.1007/S41604-017-0003-0

Zare Mehrjerdi, Y., & Nadizadeh, A. (2013). Using greedy clustering method to solve capacitated location-routing problem with fuzzy demands. *European Journal of Operational Research*, *229*(1), 75–84. https://doi.org/10.1016/J.EJOR.2013.02.013

Zeimpekis, Vasileios. (2007). *Dynamic fleet management : concepts, systems, algorithms & case studies*. 241. https://books.google.com/books/about/Dynamic_Fleet_Management.html?hl=fr&id=8LhdeoxYzLAC

Zeng, H. Y. (2019). Improved Particle Swarm Optimization Based on Tabu Search for VRP. *Journal of Applied Science and Engineering Innovation*, *6*(2), 99–103.

Zhang, H., Zhang, Q., Ma, L., Zhang, Z., & Liu, Y. (2019). A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. *Information Sciences*, *490*, 166–190. https://doi.org/10.1016/J.INS.2019.03.070

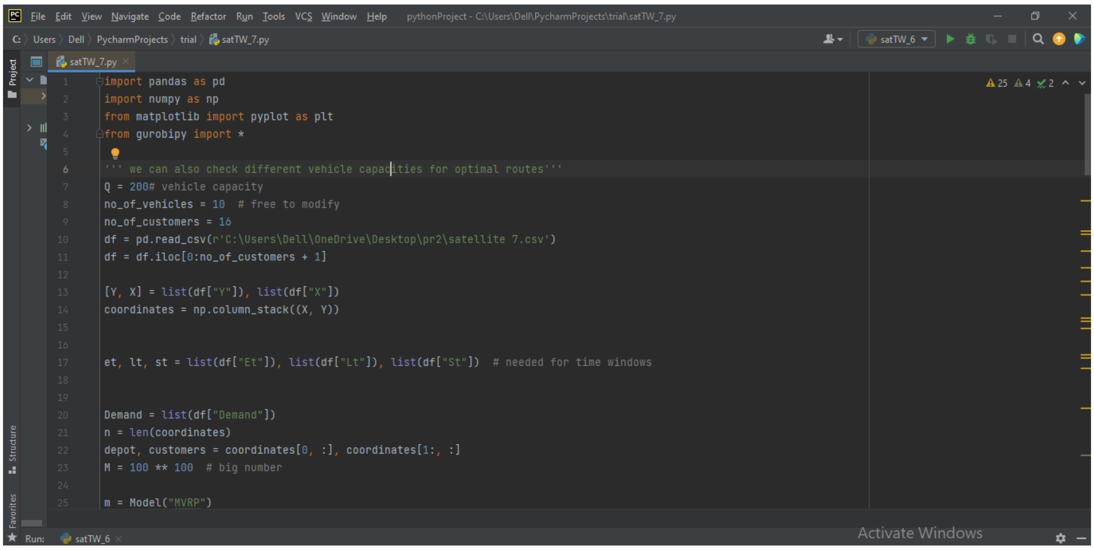
Zhang, R., Nie, F., Guo, M., Wei, X., & Li, X. (2019). Joint Learning of Fuzzy k-Means and Nonnegative Spectral Clustering With Side Information. *IEEE Transactions on Image Processing*, *28*(5), 2152–2162. https://doi.org/10.1109/TIP.2018.2882925

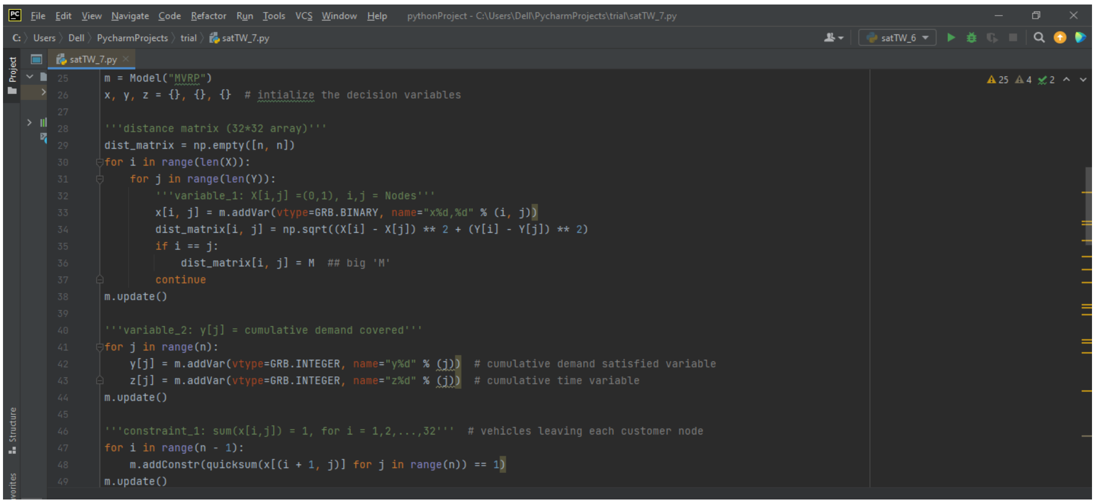
Zhang, X., Chen, L., Gendreau, M., & Langevin, A. (2021). Learning-Based Branch-and-Price Algorithms for the Vehicle Routing Problem with Time Windows and Two-Dimensional Loading Constraints. *Https://Doi.Org/10.1287/Ijoc.2021.1110*, *34*(3), 1419–1436. https://doi.org/10.1287/IJOC.2021.1110

Zhu, L., Rousseau, L. M., Rei, W., & Li, B. (2014). Paired cooperative reoptimization strategy for the vehicle routing problem with stochastic demands. *Computers & Operations Research*, *50*, 1–13. https://doi.org/10.1016/J.COR.2014.03.027

APPENDIX

Appendix A - Algorithms for VRP using Python programming language





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satTW_7.py

```python
m.update()

''' constraint_2: sum(x[i,j] =1 for j = 1,2,.....,32)'''  # vehicles arriving to each customer node
for j in range(n - 1):
    m.addConstr(quicksum(x[(i, j + 1)] for i in range(n)) == 1)
m.update()

'''constraint_3: sum(x[0,j]) = 5'''  # vehicles leaving depot
m.addConstr(quicksum(x[(0, j)] for j in range(n)) == no_of_vehicles)
m.update()

'''constraint_4: sum(x[i,0]) = 5'''  # vehicles arriving to depot
m.addConstr(quicksum(x[(i, 0)] for i in range(n)) == no_of_vehicles)
m.update()

''' Either of the constraint_5 or the constrain_6 can eliminate sub-tours independently'''

'''constraint_5: capacity of vehicle and also eliminating sub-tours'''
for j in range(n - 1):
    m.addConstr(y[j + 1] <= Q)
    m.addConstr(y[j + 1] >= Demand[j + 1])
    for i in range(n - 1):
        m.addConstr(y[j + 1] >= y[i + 1] + Demand[j + 1] * (x[i + 1, j + 1]) - Q * (1 - (x[i + 1, j + 1])))
m.update()
```

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satTW_7.py

```python

'''constraint_6: time-windows and also eliminating sub-tours'''


for i in range(n - 1):
    # assumption: service starts at 9:00 AM, 9 == 0 minutes, each hour after 9 is 60 minutes plus previous hours
    m.addConstr(z[i + 1] >= (et[i + 1] - 9) * 60)  # service should start after the earliest service start time
    m.addConstr(z[i + 1] <= (lt[i + 1] - 9) * 60)  # service can't be started after the latest service start time
    for j in range(n - 1):
        # taking the linear distance from one node to other as travelling time in minutes between those nodes
        m.addConstr(z[i + 1] >= z[j + 1] + (st[j + 1] + dist_matrix[j + 1, i + 1]/100) * x[j + 1, i + 1] - M*(1-x[j+1, i+1]))
m.update()


'''objective function'''
m.setObjective(quicksum(quicksum(x[(i, j)] * dist_matrix[(i, j)] for j in range(n))*50+1000 for i in range(n)), GRB.MINIMIZE)
m.update()

'''optimize'''
m.optimize()

'''retrieve the solution'''
sol_y, sol_x, sol_z = m.getAttr('x', y), m.getAttr('x', x), m.getAttr('x', z)
X, Y, Z = np.empty([n, n]), np.empty([n]), np.empty([n])
for i in range(n):
```

File Edit View Navigate Code Refactor Run Tools VCS Window Help pythonProject - C:\Users\Dell\PycharmProjects\trial\satTW_7.py

satTW_7.py

```python
'''retrieve the solution'''
sol_y, sol_x, sol_z = m.getAttr('x', y), m.getAttr('x', x), m.getAttr('x', z)
X, Y, Z = np.empty([n, n]), np.empty([n]), np.empty([n])
for i in range(n):
    Y[i] = sol_y[i]
    Z[i] = sol_z[i]
    for j in range(n):
        X[i, j] = int(sol_x[i, j])
print('\nObjective is:', m.objVal, 'LKR')
print('\nDecision variable X (binary decision of travelling from one node to another):\n', X.astype('int32'))
print('\nDecision variable z:(service start time of every customers in minutes)\n', Z.astype('int32')[1:])
print('\nDecision variable y (cumulative demand collected at every customer node):\n', Y.astype('int32')[1:])


def plot_tours(solution_x):
    tours = [[i, j] for i in range(solution_x.shape[0]) for j in range(solution_x.shape[1]) if solution_x[i, j] ==1]
    for t, tour in enumerate(tours):
        plt.plot(df["X"][tour], df["Y"][tour], color = "black", linewidth=0.5)
    plt.scatter(df["X"][1:], df["Y"][1:], marker = 'x', color = 'g', label = "customers")
    plt.scatter(df["X"][0], df["Y"][0], marker = "o", color = 'b', label = "Satellite 7")
    plt.xlabel("X"), plt.ylabel("Y"), plt.title("Tours"), plt.legend(loc = 4)
    plt.show()


plot_tours(X)
```