Decision support tool for strategic performance evaluation of urban transshipment network with electric freight vehicles in low emission zones

MSc Complex systems engineering and management

A.R.B Nallapeta

Decision support tool for strategic performance evaluation of urban transshipment networks with electric freight vehicles in low emission zones.

Master thesis submitted to Delft University of Technology

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

In Complex systems engineering and management

Faculty of Technology, Policy, and Management

By

A.R.B Nallapeta

Student number: 4755367

To be defended in public on 07 15 2020

Graduation committee

Chairperson : Prof. dr. ir. L.A. Tavasszy, Transport and Logistics
First Supervisor : Dr.M.Y. Maknoon, Transport and Logistics
Second Supervisor : Dr. H.H. Hansen, Energy and Industry
External Supervisor: Dr.T.G.H. Teoh, Panteia

PREFACE

This thesis is the final product of the master's in science program 'Complex systems engineering and management' in the track of transport and logistics. It involves the development of a model-driven decision support system that assists logistics practitioners to evaluate the performance of urban transshipment network with electric freight vehicle in providing last-mile delivery service to customers located in low emissions zones. The decision to follow this topic is the result of my drive to make existing logistics operations sustainable in the coming years. I hope that my research will allow logistics service providers to realize the potential of sustainable logistics networks for their operations.

I would like to express my gratitude to the supervision committee, as their support has helped to ensure a steep learning curve during the entire research process. My sincere gratitude to Lóri Tavasszy for helping me frame the research into an exciting systems-level project. To Yousef Maknoon, for patiently listening to my ideas and sharing his expertise at every stage of the research process. To Helle Hansen for the excellent assistance and willingness to support throughout the entire journey. I cannot thank you enough for your words of support and trust in my work.

I feel fortunate for having the opportunity to conduct my research together with Panteia, and for having met many great people during the journey. I want to thank Tharsis Teoh specifically for assisting me with all the challenges encountered during the research process and his concern towards preparing me for my career. Without his time and patience, I would not have achieved so much. Additionally, I want to thank Arnaud Burgess, for welcoming me into his team, for all the friendly chats at the office and the words of support.

Lastly, I am incredibly thankful to my parents, who spared no effort to support me. My gratitude goes to them for always believing in my potential and encouraging me to keep pursuing my dreams. A special thank you to my friend Maarten Nepveu for helping me throughout the whole master journey and, of course, to all friends that have accompanied me throughout my journey and made the journey more pleasant.

I hope you enjoy reading it.

Arjun Ramesh Babu Nallapeta
Delft, July 2020

SUMMARY

A transshipment network involving small urban logistics facilities for deconsolidation and transfer of shipments from high capacity freight vehicles to smaller vehicles is called an urban transshipment network. These networks, when used for last-mile logistics, enable the usage of light electric freight vehicles in urban areas. In this way, these networks can be employed by logistics service providers (LSPs) to cope with the new low emission zone policies in dense municipalities. However, to ascertain the capabilities of these networks, LSPs will be tending to virtually evaluate their performance towards the fulfillment of their strategic business goals and juxtapose them with other plausible network alternatives. This evaluation process is complicated as it is necessary to simulate how urban transshipment networks will be configured to fulfill customers within low emission zones and, additionally, obtain data about the resulting distribution activities. Considering that an LSP will only consider adopting that configuration of a logistics network which minimizes the total logistics costs (TLC), combinatorial optimization models such as location routing problem (LRP) models can be employed to deal with the issue mentioned above. However, the existing models of location routing problem cannot be used for the real-life problem due to their computational complexity. Thus, the goal of this research is to assist LSPs in strategic evaluation of urban transshipment networks while circumventing the difficulties associated with traditional LRP models. Therefore, the following research question was formulated to achieve this goal:

How to evaluate the performance of urban transshipment network with electric vehicles for last-mile delivery services within a low emission zone?

To answer the above research question, a model-driven decision support tool is developed to strategically evaluate urban transshipment networks and compare their performance against other possible networks. Subsequently, the proposed tool is applied to a synthetic case study to demonstrate its ability to handle real scale problems. The general framework for the tool is presented in Figure 1, followed by the explanation of distinguishable steps in the decision support tool.

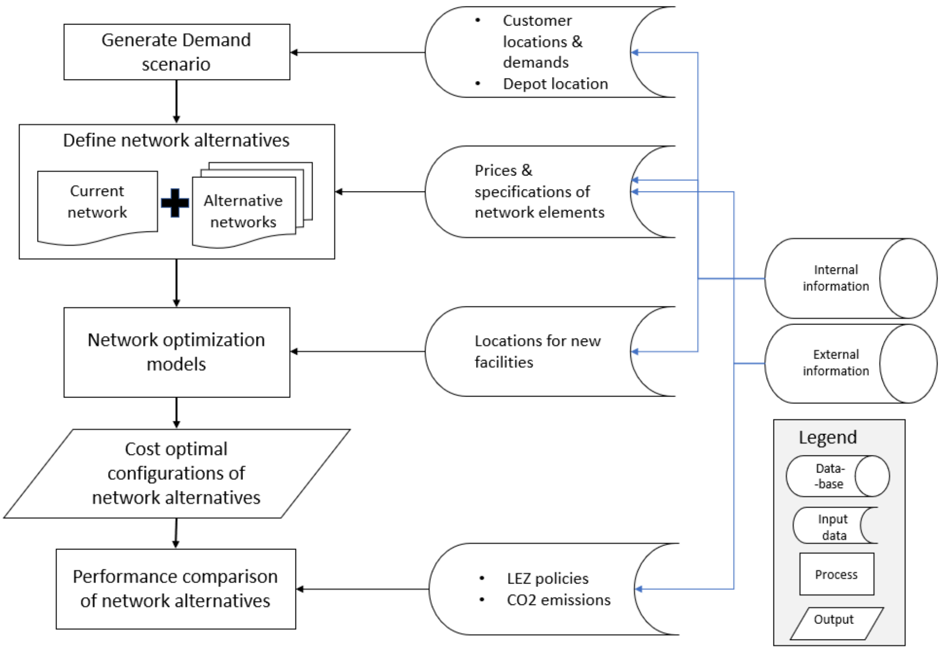


Figure 1: General framework of the decision support tool

1. Generate demand scenario: This is the preliminary step that utilizes LSP's customer data set to reproduce the service needs of customers inside a low emission zone on a typical working day. The service needs can represent either present demand or future projections.
2. Define network alternatives: In this step, the structure of networks that can alternatively be adopted by the LSP for last-mile operations are clearly defined. These networks include the urban transshipment type networks as well as the current conventional network. Additionally, the operating costs and constraints of the functional elements used within these network alternatives are derived from their respective prices and specifications.
3. Network optimization models: The configuration that fulfils the demands scenario with minimum TLC is determined for all the defined network alternatives using a set of optimization models. A new model, based on continuous approximation (CA) methods, is used explicitly for urban transshipment networks, and the existing optimization model is used for conventional network types.
4. Performance comparison: Using the cost-optimal configurations of network alternatives and corresponding distances traveled by the vehicles, key performance indicators from economic, environmental, operational, and social perspectives are measured and compared between network alternatives.

The proposed decision support system is applied to a case study that is synthetically created using multiple information sources and assumptions. For generating demand scenarios, instances for vehicle routing problems from Uchoa et al. (2017) is used to replicate the locations and demands of customers within a low emission zone. Three demand scenarios are created such that customer densities increase linearly across them. The prices and specifications of vehicles and micro hubs in network alternatives were obtained from Panteia's total cost of ownership model and Balm et al. (2018), respectively. Prospective micro hub locations were randomly selected from the demand scenarios, and input parameter values for measuring KPIs are derived from previous relevant studies and reports.

The results of the case study have demonstrated the capability of the proposed CA-based optimization model for producing near-global cost-optimal configurations of urban transshipment networks and replicating distribution activities on an aggregate level. The results from the performance comparison process indicate that the customer density within a low emission zone is an essential factor that affects the overall performance of urban transshipment networks. The performance of the urban transshipment seems to increases significantly with an increase in customer density compared to that of conventional networks. Furthermore, the results also show that locating the micro hubs inside the low emission zone helped in further enhancing the performance of urban transshipment networks

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

2E-LRP: Two echelon location routing problem

ARCE: Augmented routing cost estimation formula

Alt: Alternative

CA: Continuous approximation

CVRP: Capacitated vehicle routing problem

DST: Decision support tool

EFV: Electric freight vehicle

FLP: Facility location problem

ICEV: Internal combustion engine vehicles

KPI: Key performance indicator

LRP: Location routing problem

LSP: Logistic service provider

LEZ: Low emission zone

MAR: Minimum area rectangle

MPDS: Minimum LEZ penalty on diesel vans to shift from alternative 1

OR: Operation research

POD: Point of delivery

TCO: Total cost of ownership

TLC: Total logistics costs

TSP: Travelling salesmen problem

VRP: Vehicle routing problem

WTW: well to wheel

1 INTRODUCTION

In this chapter, the motivation and the content of the thesis are discussed. The problem that is being addressed within this research is first explained, and then research objectives are discussed.

1.1 PROBLEM DEFINITION:

Transshipment network is an existing practice in the logistics sector, in which goods are shipped to an intermediate logistics facility or a hub before transporting them to their final destination (Huber et al., 2015). The purpose of doing so is to either change transport modes, consolidate, or de-consolidate shipments at these intermediate facilities. The urban transshipment network is a new adaption of the above logistic practice for last-mile distribution in dense metropolitan regions. In this network, a set of micro hubs located in the urban areas are used for deconsolidating shipments and transferring them from high capacity vehicles to light freight vehicles that deliver to customer locations (Merchan et al., 2016). It is essential to note that these micro hubs are storage facilities with a smaller physical footprint dedicated purely for mode shift rather than storage purposes. Furthermore, the concomitant short distances between micro hubs and customer locations facilitate the utilization of light electric freight vehicles (LEFV) with zero tailpipe emissions and limited driving ranges to perform deliveries from micro hubs (Quak, Nesterova, & Van Rooijen, 2016).

Over the past decade, expansion in last-mile delivery services and the increased emissions in cities is forcing municipalities to introduce low emission zone (LEZ) in high-density urban areas to limit access to diesel-powered cargo vehicles (Dablanc & Montenon, 2015a). Consequently, the existing conventional networks of logistics service providers (LSP) must be changed to provide last-mile delivery services within LEZs. These adaptations to the logistics networks must ensure that the operations will comply with such LEZ regulations. Urban transshipment networks, in conjunction with LEFVs, offer a potential solution for LSPs to perform uninterrupted operations in LEZ. The reason is that LEFVs, being fully electric, generally meet the entry requirements of LEZ. However, these new network demands significant resources of an LSP in the form of micro hubs establishment and LEFV fleet acquisitions. Therefore, private LSPs must assess the performance of these new networks towards achieving their economic, environmental, and operational objectives before deciding to adopt them over existing conventional ones (Gunasekaran et al., 2004).

Deriving insights about a new logistics network's performance before its application is somewhat complicated. The reason is that the configurations of these networks, which affects the overall distribution process, is not known in advance. A configuration of an urban transshipment work is characterized by the size, location, numbers of micro hubs, and fleet sizes of the cargo vehicle fleets (Merchan et al., 2016). From all possible network configurations, it is apparent that a private LSP would consider choosing only that configuration, which minimizes the costs (Rybakov, 2017). For this reason, network design optimization models play an essential role, as they can reproduce analytically the cost-optimal network configuration that is likely to be adopted by LSP and information about the resulting distribution activity (Amodeo et al., 2015).

Particularly for urban transshipment networks with LEFVs, finding cost-optimal network configurations involves two strategic network design decisions, micro hub locations, and LEFV fleet sizes at micro hubs. Facility location problems are a specific type of combinatorial optimization problem that can be used to determine the optimal locations for the micro hubs such that customers are as close as possible to any micro hub (Škrinjar et al. 2012). Nevertheless, locations of logistics facilities such as hubs will directly affect the routes of freight vehicles. This interrelationship is ignored in typical facility location problems. For this reason, the optimal micro hub locations and required fleet sizes of LEFVs for urban transshipment networks must be found in an integrated approach that integrates vehicle routing aspects into the facility location problem. The location routing problem (LRP) model is another type of combinatorial optimization problem that is capable of coping with the above interrelationship while determining cost-optimal configurations of urban transshipment networks (Prodhon & Prins, 2014). However, these LRP models combine two NP-hard problems, namely facility location problem and vehicle routing problem (Nagy & Salhi, 2006). Consequently, the existing LRP models are computationally complex, causing their limited application to real-life contexts (Cuda et al., 2015a). However, parsimonious techniques like continuous approximation (CA) have shown to alleviate the complexity of these models, especially at the routing level, to provide near-optimal solutions for large scale real-world problems (Ansari et al., 2018).

Thus, the overall challenge for an LSP is to evaluate the performance of urban transshipment networks to serve a particular LEZ by employing CA-based network optimization models. Moreover, the evaluation must encompass all the different objectives relevant to freight transportation businesses such that the network's performance is analyzed from a strategic decision-maker's perspective. The clear objective of this research and the adopted approach is elucidated in the following sections.

1.2 RESEARCH OBJECTIVE

The overall aim of this study is to address the problem of how to strategically evaluate the performance of urban transshipment networks with LEFVs for last-mile operations in a LEZ. Insights from research in four broad topics justify the objective of this research. Firstly, the application of electric freight vehicles (EFV) in last-mile logistics is brought to attention, with its limitations leading to the idea of integrating them with the transshipment facilities. Secondly, the feasibility of urban transshipment networks is analyzed based on previous pilots and tests, where the importance of virtually assessing the performance of these new logistics networks before conducting full-scale tests or pilot is highlighted. Next, the different types of LRP models are investigated to understand their working and limitations, indicating the need for simpler models. Finally, the literature pertinent to performance evaluation of logistics networks is discussed, leading to methods and metrics for measuring the network's performance. Hence the research aims to assist LSPs in the strategic assessment of urban transshipment networks with LEFVs for last-mile operations.

1.3 RESEARCH QUESTIONS

The following research question has been formulated to fulfill the research objective:

How to evaluate the performance of urban transshipment network with electric vehicles for last-mile delivery services within a low emission zone?

As this question involves a set of different processes, it is required to develop a set of sub-questions which guides the research towards answering the central question:

1. What are the main criteria to evaluate the performance of the urban transshipment network from the perspective of a private logistics firm?

2. What information is required to evaluate the performance of urban transshipment networks?

3. What is the baseline for evaluating the performance of the urban transshipment network?

4. Which analytical model is required to derive the information required for evaluating the performance of the urban transshipment network?

1.4 APPROACH

To answer the above research questions, a model-driven decision support tool (DST) is proposed to measure the performance of urban transshipment networks and compare them against conventional networks. These conventional networks utilize only a fleet of freight vehicles to perform direct deliveries from depot to customer locations. Additionally, the DST considers different plausible ways in which logistics networks can be organized. The DST analyses the performance of the logistics networks based on their cost-optimal network configuration that is found using network optimization models. Classic optimization models are adopted for determining cost-optimal configurations of conventional type networks, while a novel CA-based model is developed specifically for urban transshipment networks. The DST is presented as a sequential framework, which guides LSPs to analyze the performance of urban transshipment networks for their last-mile operations. Finally, the proposed DST is applied to a synthetic case study to demonstrate its capabilities.

1.5 THESIS STRUCTURE:

The structure of the thesis is as follows: Chapter 2 presents the reviewed literature relevant to the research question. Chapter 3 presents the methodology adopted in this research. Chapter 4 explains the application of the DST to a synthetic case study. Following the application, Chapter 5 discusses the results of the case study. Finally, Chapter 6 discusses the findings, conclusions, and future research recommendations.

2 LITERATURE SURVEY

In this chapter, all background information essential for understanding the motivation behind this research and the field of application is discussed. The related literature is classified into four main sections: Last mile distribution with EFVs (Section 2.1), Transshipment networks with LEFVs and micro hubs (Section 2.2), Network design of transshipment networks with LEFVs (Section 2.3). Performance evaluation of last-mile logistics (Section 2.4). Finally, all the identified literature is synthesized in Section 2.5.

2.1 LAST-MILE DISTRIBUTION NETWORKS WITH EFVS

Seeing that electric freight vehicles (EFV) have been gaining the attention of both public and private organizations for mitigating negative externalities of urban logistics, several science researchers have focused on various aspects relevant to EFVs and their applications. Recently, Wang et al. (2018) conducted a systematic literature review of 60 related scholarly works in the period between 2007 and 2018, focusing on the employment of EFVs in urban logistics. The synthesis revealed that smaller, light-duty EFV (LEFV) has the potential to compete with internal combustion engine vehicles (ICEVs) better than the medium or large EFVs. LEFV are defined as " EFVs that weigh (gross vehicle weight) less than 3.5 tons such as electric cargo bikes, electric cargo bicycles/tricycles, and small distribution electric vehicles" (Hogt et al., 2017). Taefi et al. (2015) argue that the primary reasons for LEFV's competitiveness include lower acquisition costs, imposing less pressure on existing road infrastructure, and producing zero emissions.

Oliveira et al. (2017), through a state-of-the-art review on freight transport modes in urban logistics, concurred that in the future, LEFVs are likely to replace conventional ICE vehicles in the last-mile distribution. The authors claim that their characteristics, such as limited driving ranges and limited driving ranges, suit the requirements in last-mile delivery services. Similarly, Reiter & Wrighton (2017) reported the results of the EU funded project 'Cyclelogisitcs.' The calculations reveal that around 31% of the urban goods transport in European cities can be shifted to electric cargo cycles. Few researchers have relied on practical methods by analyzing, ex-post, pilots, and practical demonstrations to draw insights about LEFVs feasibility. For instance, Balm et al. (2018) examined 30 LEFV projects that were carried out in the Netherlands under the LEVV LOGIC project. The study concludes that LEFV has high potential in delivering food, parcel, or courier but does not show much promise in providing truckload volumes required for B2B Transaction. From a vehicle design standpoint, Hogt et al. (2017) analyzed the projects under LEVV logic to present with an optimal design of LEFVs for automotive makers. Their results indicate that feasible LEFVs designs are usually suited for delivering small packages or couriers in congested spaces. Thus, LSP engaged in delivering parcels to customer locations in urban areas can explore logistics concepts with LEFVs. Nevertheless, despite having great potential, the viability of LEFVs in last-mile delivery is still disputable and varies case by case basis.

For providing evidence for the adoption of LEFVs, few scientific studies focus on the ex-ante evaluation of LEFV based logistic schemes through simulation, and optimization methods (Duarte et al., 2016; Gruber & Narayanan 2019; Lebeaue et al., 2019; Lebeau et al., 2015; Melo & Baptista 2017). From these studies, it was evident that LEFV fleets work efficiently in time-critical deliveries and that their costs can be lower than diesel-powered fleets provided their utilization is at the maximum level. However, results from Melo & Baptista (2017) show that small ranges and lower payload capacities restrict LEFVs application. The authors stress on additional network adaptations for adopting LEFVs into operations. Therefore, the above literature indicates that adaptations to existing logistics concepts are necessary to utilize LEFVs into last-mile operations.

2.2 TRANSSHIPMENT NETWORK WITH LEFVS FOR THE LAST MILE DISTRIBUTION

Moolenburgh et al. (2019) analyzed all the logistics concepts utilized with 8 LEVV-logic projects. They showed that LEFV is a solution alongside other solutions such as mixed vehicle fleets (both LEFV and ICE vehicles) and two-echelon distribution networks with transshipment points. In the latter case, conventional diesel-powered high capacity vehicles usually delivered truckload freight volumes to transshipment points, where they are deconsolidated and then transported to individual customer points through LEFVs. However, transshipment points must be located close to or within the city because LEFVs have a limited driving range. This two-echelon distribution network is in line with a past study by Lenz & Riehle (2013), where authors advocate for the use of transshipment facilities to enable urban goods delivery with LEFV.

Leonardi et al. (2012) and Van Duin et al. (2013) analyzed two successful LEFV demonstrations in London and Amsterdam, respectively. In these cases, LEFV fleets, including tricycles, vans, and quads trailers (the cargohopper), are used in conjunction with micro-urban deconsolidation centers. These analyses give valuable insights and lessons for logistics decision-makers to test such logistic concepts into their business. However, conducting such practical demonstrations and experiments requires a substantial allocation of the company's resources. Moreover, the success of such varies on a case by case basis. Hence, before carrying out pragmatic assessments, the ex-ante analysis of networks with LEFVs and transshipment facilities must be carried out. These analyses allow logistics decision-makers to check beforehand if such networks are potentially viable for their businesses. Reporting in the scientific literature for an ex-ante assessment of such logistics schemes is limited.

Despite leading to additional investments for establishing transshipment facilities and acquiring additional cargo vehicles, Guerrero & Díaz-Ramírez (2017) suggest that if the transshipment network is designed in the right manner, they could reduce the overall total logistics costs (TLC) for an LSP compared with conventional networks. The authors consider the general structuring of TLC proposed by (Abdallah 2004) in their study, as shown in Table 2-1. To our best knowledge, ex-ante evaluation studies of transshipment networks based on their minimum TLC configurations are limited in the literature.

Table 2-1:Break down of total logistics costs (Abdallah, 2004)

	Costs associated with	
Number of vehicles- day	• Vehicle depreciation costs	➢ Fixed
	• Insurance, road tax	➢ Fixed
	• Salary costs for drivers	➢ Fixed
Total kilometres	• Fuel cost	➢ Variable
	• Maintenance cost	➢ Variable
Warehouse operating	• Building and equipment costs	➢ Fixed
	• labour costs	➢ Variable

2.3 DESIGN OF TRANSSHIPMENT NETWORKS WITH LEFVS

As discussed in the previous sections, cost-optimal configurations of urban transshipment networks should be determined as they act as the basis for performance evaluation. Simoni et al. (2018) proposed a simple sequential approach to obtain the configuration of micro depots for a mail delivery company that results in minimum overall costs. In this approach, firstly, the optimal locations for micro depots (used for cross-docking) are determined and, afterward, optimal vehicle fleet numbers and routes for customer deliveries at each of these micro depot locations are determined. Although this method can be used in other contexts for similar micro depot measures, the approach neglects the effect of micro depot locations on vehicle fleet sizing and routing.

In operation research (OR), intermediate logistics facilities such as micro depots, are termed as 'hubs.' OR models that account for interdependencies between hub location and vehicle routing to find the optimal configuration of network with hubs are popularly known as location routing problems (LRP) (Aykin, 1995). In contexts where goods flow occurs in two distinct echelons, as in the case of an urban transshipment network, the LRP is termed a Two-Echelon LRP (2E-LRP) (Drexl & Schneider, 2015). The first echelon flow of goods is between faraway storage depots to intermediate micro hubs, whereas the second echelon deals with goods delivery from micro hubs to customer locations. 2E-LRP aims at finding the locations for hubs among candidate locations and simultaneously determine the routes of the vehicle fleet at both echelons, such that the value of the objective function is either minimized or maximised (Crainic et al., 2010).

2.3.1 Modelling and solving 2E-LRP

Cuda et al. (2015) reviews various past modelling and solving approaches for 2E-LRP. According to the authors, the objective function of a 2E-LRP usually involves logistics cost components, and capacitated 2E-LRP models (accounting for capacity constraints for facilities and vehicles) are the most prominent in the literature.

Intially, Boccia et al. (2010) formalized the 2E-LRP, and later, Crainic et al. (2011) proposed three multi integer formulations for the 2E-LRP and solved them using a commercial solver. The exact approach was capable of solving small instances consisting of not more than 25 customers, and when used on more extensive problems, the solution gaps were as high as 25%. Contardo et al. (2012) proposed a two index multi integer linear 2E-LRP formulation that was strengthened by a family of inequalities. The authors developed a branch and cut algorithm to solve the model on CPLEX. This method could solve the problem with 50 customers and is recognized as the best in a class of exact methods for solving a 2E-LRP (Contardo et al., 2013). The inability to solve realistic large 2E-LRPs with exact methods is because these problems are NP-hard as it constitutes of two other NP-hard problems; facility location and vehicle routing problems (Cuda et al.,2015).

Since exact methods alone are incapable of solving large 2E-LRPs, the majority of researchers have drawn focus to (meta-) heuristic methods. Boccia et al. (2010) proposed a tabu search method that decomposes the 2E-LRP problem into two subproblems: facility location problems (FLP) and vehicle routing problem (VRP) (at both the echelon). A similar approach was adopted by Gao et al. (2016), where they used K means clustering and Ant colony optimization for solving an FLP and VRP, respectively. Nugen et al. (2012a, 2012b) propose two heuristic procedure greedy randomized adaptive search procedure (GRASP) and a multi-start iterated local search (MS-ILS). Contardo et al. (2012) proposed an adaptive large-neighborhood search (ALNS) meta-heuristic to find, in reasonable times, good quality solutions for instances with 200 customers. However, in real-life applications, the size of LSP operating within an entire city corresponds to larger problem instances than above. Notably, the routing aspect, which involves many small vehicles and hundred of customers per square kilometer, will render the corresponding 2E-LRP intractable (Cuda et al. 2015).

Winkenbach et al. (2016), in cooperation with French PO- 'La Poste,' demonstrated a different approach to resolve a 2E-LRP model by using a continuous approximation (CA) techniques. The cost of LEFV routes in the second echelon was approximated using route length estimation formulas instead of finding the explicit routes of vehicles in the second echelon through VRP formulations. The authors argue for this method as routing decisions in operational levels play a secondary role when LRP is used for strategic network design. However, the approach ignores the spatial distribution of the customer points by dividing the entire problem instance equally to rectangular spaces with uniform distribution of customers. This assumption could result in more travel distances and consequently increase fleet sizes of electric vehicles, which have limited driving ranges. To our best knowledge, aside from Winkenbach et al., (2016), studies adopting CA approaches to solve 2E-LRP have not been conducted in the past.

2.3.2 CA approaches in place of VRPs

The first CA method to solve approximately a traveling salesman problem (TSP) and find the optimal travel distance or costs was proposed by Beardwood et al. (1959). Daganzo (2005) extended the approach for solving complex VRP problems where a set of vehicles are used in deliveries. Winkenbach et al. (2016) adopted this method for resolving the 2e-LRP. Figliozzi (2008) proposed a refinement of the approximation to Daganzo (2005). The model assumed that the number of customers or quantities delivered by capacitated vehicles is balanced. Regression studies have shown that the model by Figliozzi (2008) provides reasonable predictions for the average tour length for a variety of VRP problem instances in urban freight distribution contexts (Davis & Figliozzi, 2013). According to this model, the average total distance traveled by all delivery vehicles within a service region (denoted as Td) is approximated by the following formulae:

$$Td = k_1 \frac{n-N}{N} \sqrt{n.A} + k_2.N$$

Where 'n' is the number of delivery points (customer point), 'A 'is the area for service region 'N 'represents the number of vehicles used for servicing. Constant 'k_1' is the local tour parameter, which is obtained through linear regression, while' k_2' is the distance between the depot to the center of the service region. In case the depot is at the center of the service region, Then the value of k_2 can be equated to zero, and the second term can be ignored.

2.4 PERFORMANCE EVALUATION

Olsson et al. (2019) recently performed a systematic literature review of all research relevant to last-mile logistics. The authors found that many articles had focussed on evaluating the performance of different aspects of last-mile logistics. Four performance themes were presented, which included economic, environmental, customer satisfaction, and policy effectiveness in last-mile logistics. From an economic standpoint, Cleophas & Ehmke (2014) focussed on the value of the last mile deliveries and the requirement to actively measure the overall and average individual cost of deliveries. Van Loon et al. (2015) developed a life cycle analysis model to compare the CO2 emissions of different fulfillment methods in the retail industry. Their study showed that last mile deliveries for online retail purchases performed poorly from an environmental perspective as they resulted in significant local CO2 emissions.

Few researchers have focused on the performance of last-mile networks from a customer perspective by analyzing service time and service qualities (Buldeo et al. 2019; Huang et al. 2009). On the other hand, Seebauer et al. (2016) have evaluated the effectiveness of polices in last-mile logistics, such as entry restrictions, financial incentives.

2.5 SYNTHESIS OF LITERATURE AND KNOWLEDGE GAPS

The conclusion that can be drawn from the above literature review is that evaluating the performance of the transshipment network with LEFVs is crucial for their future adoption into urban logistics. As discussed in Section 2.1, EFVs, especially the lighter variants (LEFVs), can potentially replace diesel vehicles in last-mile delivery services but restrict their flexibility of operations. The reason is that a single echelon distribution system, typically used in conventional logistics systems, impede the usage of limited driving range vehicles due to the considerable travel distances between depot location and customer service regions. Circumventing these limitations will require additional changes to existing logistics concepts. For this reason, the current research focuses on a new adapted logistics solution to alleviate the limitations of LEFVs and allow them to be used flexibly in last-mile delivery operations. This new concept involves the usage of micro transshipment facilities in proximity to customer points.

Few practical demonstrations and pilots are conducted in the past with urban transshipment networks, as seen in Section 2.2. These studies show that the feasibility of such networks varies case to case basis, and it is uncertain for LSPs if these new networks are for their business before conducting expensive pilots. Thus, this research focuses on assisting LSP to evaluate, analytically, if urban transshipment networks with LEFVs are viable for their business. Moreover, few studies show that optimum designs of urban transshipment networks can result in a lesser TLC for LSPs compared to that of conventional networks. Thus, this research focuses on evaluating the performance of urban transshipment networks based on their minimum TLC configuration.

Section 2.3 shows that existing models for finding these above cost-optimal configurations of urban transshipment networks are computationally hard as they merge two explicit NP-hard problems, forcing researchers to develop simpler models that can be used for real-world problems. Winkenbach et al. (2016) demonstrated how a CA-based model could be used to obtain near-optimal solutions for large size problems with lower computational times, illustrating the need for more CA-based models. Thus, this research proposes a novel CA-based model that alleviates the complexity of traditional 2E-LRP models while accounting for the relationship between facility location and vehicle routing decisions.

Section 2.4 shows all the different perspectives in which the last mile distribution networks can be evaluated at strategic business levels. Inspired from these studies, the current research contributes to the existing literature by proposing a model-driven *decision support tool* (DST) that comprehensively evaluates urban transshipment networks with LEFVs in LEZ. Economic, environmental, and operational indicators are incorporated in DST to evaluate a network's performance towards achieving typical business objectives of last-mile delivery service firms. Furthermore, a comparative analysis is incorporated in the proposed DST to compare the performance of these new networks against conventional networks that are currently being used by the LSP.

Based on all the information in the literature reviewed, the following section focuses on the development of the decision support tool for quantitative performance assessment of urban transshipment networks.

3 METHODOLOGY

This section explains the distinguishable steps in the proposed DST (as schematized in Figure 3-1). A model-driven DST, based on the works of Leonardi et al. (2015) and Frota Neto (2008), is developed to help LSPs virtually evaluate urban transshipment network for their last-mile operations in LEZ region. The required input data for each step in the DST is extracted from information sources either internally or externally available to the LSP. Upon clearly defining the current network and alternative networks, a set of optimization models determine their respective cost-optimal network configurations that fulfills previously generated demand scenario with minimum TLC. These cost-optimal configurations, later, serve as the basis for performance comparison between network alternatives.

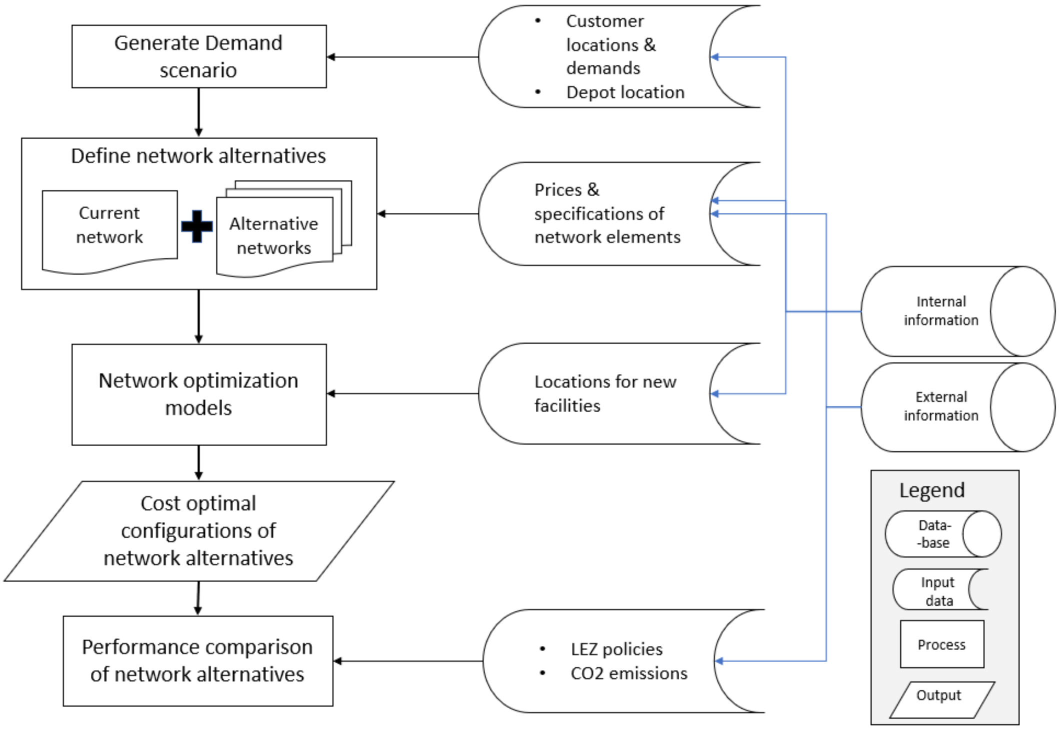


Figure 3-1: Framework of a decision support tool for performance evaluation

3.1 GENERATE DEMAND SCENARIO.

The first DST process involves reproducing customer delivery needs of an LSP for a hypothetical weekday. By sampling the real-world dataset of customers (demands and locations) located inside a LEZ, distinct demand scenarios are generated. These demand scenarios are characterized by demand density (number of customers per sq km) and average parcel specifications (size or weight of packages). Since the demand scenarios are intended for strategic level decisions, they can either reproduce existing demands or future projections. Furthermore, the location of the depot is fixed in the demand scenario because last-mile delivery concerns mainly on the parcel movement after the depot point. An example demand scenario of a hypothetical LSP is created below in Figure 3-2 to illustrate the output of the above process.

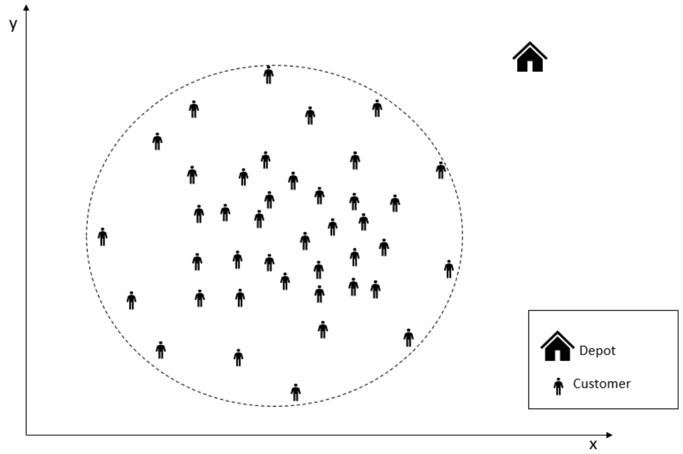


Figure 3-2:Example demand scenario

3.2 DEFINE NETWORK ALTERNATIVE

The following step in the DST involves defining different logistics networks that alternatively can be adopted by the LSP to fulfill the generated demand scenario. These network alternatives include currently employed conventional last-mile delivery network with diesel vans and three new possible substitute networks that either use electric vehicles and transshipment facilities. The structures of these network alternatives are assumed to be generalized for the proposed DSTs. In other words, the type and of freight vehicles and logistics facilities and the way each of them is organized within each network alternative are predefined. Nevertheless, the operating costs and constraints linked with these functional elements must be exogenously defined at this stage of the DST by an LSP based on their business. In the following sections, the generalized structures of these network alternatives are firstly explained, and followed by the list of parameters for network elements that should be defined for each network alternative (denoted as network alt).

3.2.1 Generalized structures of the network alternatives

As discussed in Section 2.1 and 2.2, several studies in the past have indicated the potential of last-mile logistics networks with electric vehicles (battery-electric vans, LEFVs), micro transshipment facilities, and multi-echelon distribution systems to compete with conventional networks while complying with environmental regulations. Drawing inspiration from these studies, the predefined structures for the network alternatives are shown below.

3.2.1.1 Network alternative 1 (Current network):

Network alt 1 represents the conventional network that is currently being utilized by the LSP. In this network alternative, a single echelon distribution system with a homogeneous fleet of diesel vans with fixed capacity is used for making last-mile deliveries from the depot. Each diesel van starts its routes from the depot, delivers packages to a unique set of customers in the LEZ region before returning to the depot. These diesel vehicles do not conform to entry requirements LEZ region and, as a result, receive penalties from local authorities for entering into the LEZ region. The structure of network alt 1 on the above example demand scenario (as shown in Figure 3-2) is illustrated in Figure 3-3.

<u>Distribution strategy</u>: Single echelon distribution system

<u>Vehicle fleet</u>: Homogeneous diesel vans

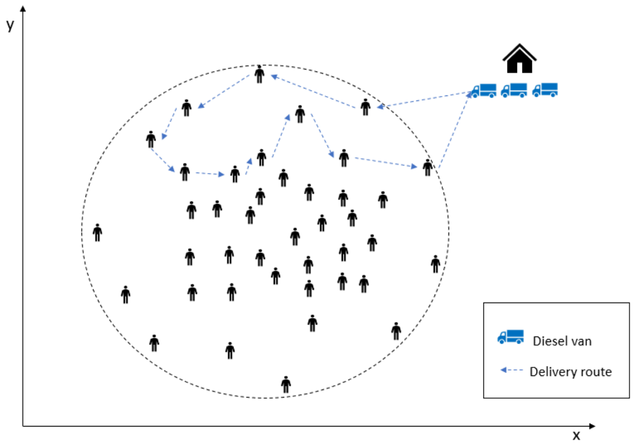


Figure 3-3: Structure of Network Alt 1

3.2.1.2 Network alternative 2

By substituting all diesel vans with battery-electric cargo vans and retaining everything else in the structure of network alt 1, a different type of structure is defined for network alt 2 (as shown in Figure 3-4). Unlike diesel vans, battery-electric cargo vans in the network alternative 2 conform to entry requirements of the LEZ region as they do not produce any tailpipe emissions. However, the ability to run these vehicles is proportional to the state of charge on the onboard battery, as they are only charged overnight at the depot (cannot be recharged in between a route)

<u>Distribution strategy</u>: Single echelon distribution system

<u>Vehicle fleet</u>: Homogeneous battery-electric cargo vans

<u>Vehicle charging strategy</u>: overnight charging

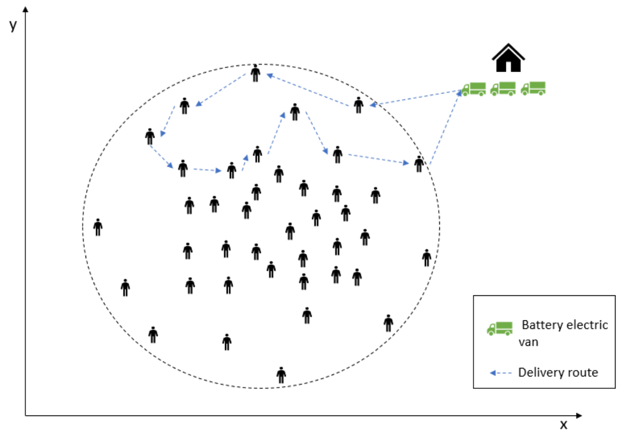


Figure 3-4: Structure of Network Alt 2

3.2.1.3 Network alternative 3

The structure of network alt 3 is based on the concept of the urban transshipment networks. In this network, diesel box trucks first transfer bundled package shipments from depot to a set of small micro hubs located at the periphery of the LEZ regions (first echelon). Subsequently, the packages arrived at each of these micro hubs are deconsolidated and shifted to LEFVs. The LEFVs then carry out routes within LEZ to deliver packages to customer locations (second echelon). These LEFVs conform to vehicle entry requirements of LEZ, and the diesel trucks in the first echelon are abstained from entering into the LEZ region. With an example route for a LEFV and a box truck, the structure of the above network alternative is illustrated in Figure 3-5.

Distribution strategy: Two echelon distribution system

Vehicle fleets: Homogeneous LEFVs and diesel box trucks

Logistics facilities: Micro hubs

Electric vehicle charging strategy: overnight charging

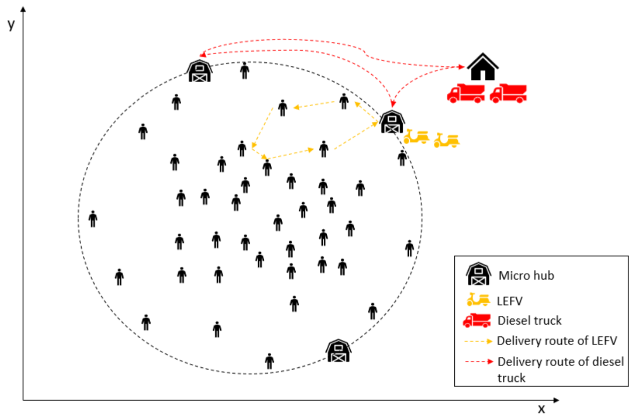


Figure 3-5:Structure of Network alt 3

3.2.1.4 Network alternative 4

By substituting all diesel box trucks with electric counterparts in the structure of network alt 3, a different type of urban transshipment network structure is proposed for network alt 4. The electric box trucks in the first echelon conform to the entry requirements of the LEZ region; thus, micro hubs can be located within the LEZ region such that they are closer to the customer locations. This structure for network alt 4 is illustrated in Figure 3-6.

Distribution strategy: Two echelon distribution system

Vehicle fleets: Homogeneous LEFVs and Electric box trucks

Logistics facilities: Micro hubs

Electric vehicle charging strategy: overnight charging

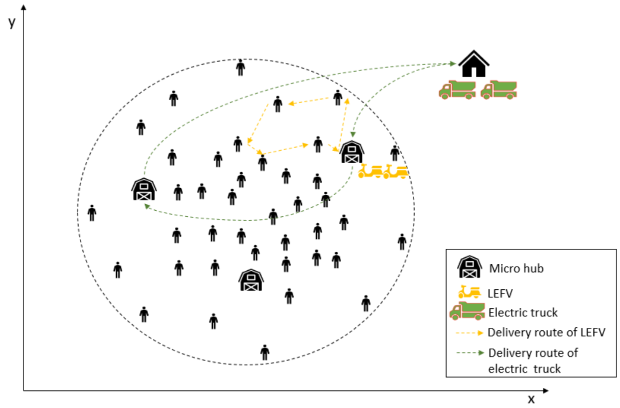


Figure 3-6: Structure of Network Alt 4

3.2.2 Operating costs and constraints of functional elements in network alternatives.

It Is evident from the previous section that various types of functional elements are being employed in the network alternatives. These elements include a range of cargo vehicles (diesel or electric vans, LEFVs, diesel or electric trucks), and micro transshipment facilities. However, there are several different options available for each of these functional elements in the market to adopt into the network alternative. For instance, several variants of LEFVs with varying prices of purchasing, payload capacities, and driving ranges are available for adoption. Based on their respective price and specifications, each of them will cost and constrain the LSP differently when adopted within network alternatives. Therefore, it is necessary to state clearly the operating costs and the constraints for each of these functional elements based on the prices and specifications of network elements that LSP decides to adopt.

Since prices and specifications of the diesel delivery vans in the current network are known before DST application, stating the operating cost and constraints of elements in the network alt 1 is derivative. However, for the other three network alternatives, the prices and specifications of the functional elements that will be employed are not given. Thus, a prior market survey for these elements must be conducted by the LSP to find suitable variants of functional elements for their demands. Upon confirming the prices and specifications of all functional elements, the list of operating costs and constraints for each of these functional elements must be defined, as shown in Table 3-1. It should be noted that the costs and capacities of every micro hub are assumed to be the same. For diesel or electric box trucks, only the costs proportionate to their usage is considered in the form of utilization cost. The reason is that box trucks, unlike LEFVs or delivery vans, are not dedicated to serving only one LEZ region but instead serving multiple LEZ regions in a day. Furthermore, the cost of charging infrastructure is calculated as a running cost by accounting it as a surcharge on the electricity cost per unit kWh.

Table 3-1: Operating costs and specifications of functional elements in network alternatives

Functional elements	Operating constraints	Operating Costs
Diesel vans	- Cargo capacity	- Daily depreciation cost (incl. insurance, road tax) - Daily labour costs/vehicle - Running cost of the vehicle (incl. fuel costs, maintenance)
Battery electric vans	- Cargo capacity - Driving range	- Daily depreciation cost (incl. insurance, road tax) - Daily labour costs/vehicle - Running cost of the vehicle (incl. fuel costs, maintenance, surcharge for charging)
LEFV		
Micro hub	Storage capacity (L)	- Daily operating cost (€) (incl. rent and Staff)
Diesel box trucks	- Payload capacity (L)	- Utilization cost (€/km) (incl. depreciation, labour, fuel)
Electric box trucks	- Payload capacity (L) - Driving range	

3.3 Define the prospective locations of micro hubs

Although the specifications and costs related to a micro hub are known, the locations where they could be established is not defined. Different barriers apply against logistic facility establishments in urban regions (public places, municipality rules, road connectivity, etc.). Thus, in the case of alternative networks 2 and 3, it is imperative to define the distinct locations within the demand scenario where micro hub establishment is possible. A sample set of prospective micro hub locations for the example demand scenario is shown below in Figure 3-7 for illustration purposes only.

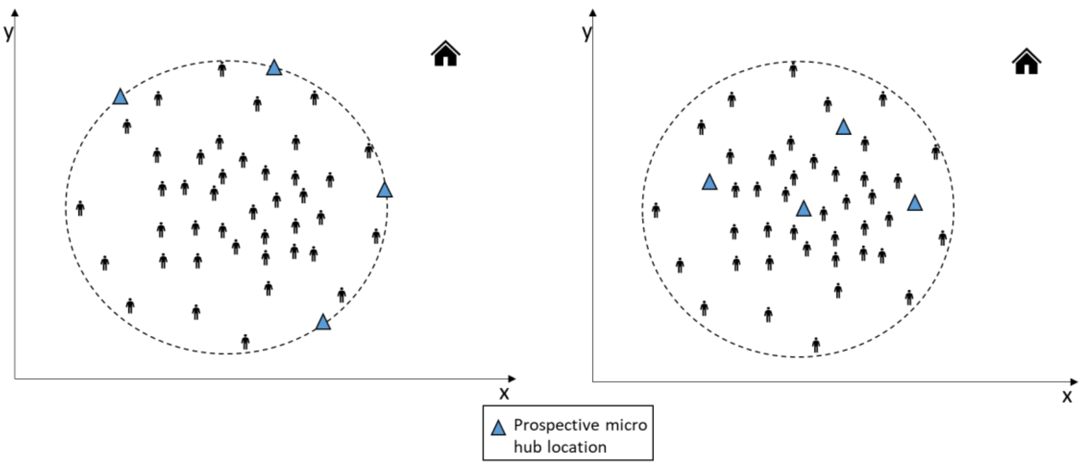


Figure 3-7: Prospective locations of micro hubs

3.4 NETWORK OPTIMIZATION MODULE

After defining all the network alternatives available for adoption, the subsequent step would be to determine the cost-optimal configurations (the numbers, locations, and sizes of functional elements) of the network alternatives to serve the generated demand scenario. The cost-optimal configuration of networks ensures that the TLC from the resulting distribution activities is minimal. As discussed in Section 2.2, TLC includes the entire range of fixed and variable costs from distribution activities, which in turn entails all operating costs associated with vehicles and micro hubs employed within a network.

A set of two different combinatorial optimization models is adopted for determining the cost-optimal configurations of network alternatives. The standard CVRP model is used for network alt 1 and 2 because both these networks employ only a single fleet of vehicles (diesel /electric delivery vans). Whereas, a new CA-based model is proposed for network alternatives 3 and 4 as they are transshipment based networks. The adopted models and their solution procedures are elucidated in the following sections.

3.4.1 Model 1- CVRP

Finding cost-optimal configurations of network alternatives 1 and 2 implies determining fleet sizes of delivery vans that minimizes the TLC. In the past, capacitated VRP (CVRP) models have been extensively employed in logistics network planning to find cost-optimal configurations of such networks. Thus, a three-index flow formulation proposed by Baldacci et al. (2004) is employed to model alternatives 1 and 2 into distinct CVRPs with TLC as the objective function. Particularly for network alt 2, a constraint to account for the limited driving ranges of battery-electric vans is added to the CVRP model. The formulation for the adopted CVRP model is explained below:

3.4.1.1 CVRP model assumptions:

The following assumptions are applicable for the adopted CVRP model;

- The customer demands are deterministic (i.e., static problem).
- The delivery route begins and ends at the depot.
- The vehicle fleets are homogeneous and capacitated.
- A single objective function that minimizes the daily total logistics cost (TLC).
- Time windows are not considered.

3.4.1.2 CVRP model notation:

The problem is described using the notations summarized in Table 3-2

Table 3-3 and Table 3-4.

Table 3-2: CVRP Sets and indices

$\boldsymbol{r}$	$\in \{1,2 \ldots, p\}$: Set of vehicles
$\boldsymbol{i}, \boldsymbol{j}$	$\in \{0,1,2 \ldots, n\}$: Set of customers and customer indexed at 0 denotes depot

Table 3-3: CVRP decision variables

$\boldsymbol{x_{rij}}$	Binary decision variable indicating if a vehicle r traverses between customers i and j

Table 3-4 CVRP input parameters

$\boldsymbol{C}$	The fixed cost of the van per day
$\boldsymbol{c}$	The variable cost of a van
$\boldsymbol{Q}$	The payload capacity of the van
$\boldsymbol{Br_{van}}$	Battery range limit of the electric van
$\boldsymbol{D_j}$	Demand of customer j
$\boldsymbol{d_{ij}}$	Distances between customer i and j

3.4.1.3 CVRP model formulation:

Minimize

$$\sum_{r=1}^{p}\sum_{j=1}^{n} C * x_{r0j} + \sum_{r=1}^{p}\sum_{i=0}^{n}\sum_{j=0,i\neq j}^{n} d_{ij} * x_{rij} * c \qquad (1)$$

Subject to

$\sum_{r=1}^{p}\sum_{i=0,i\neq j}^{n} x_{rij} = 1,$ $\quad \forall j \in \{1, \dots, n\},$ (1.1)

$\sum_{j=0}^{n} x_{r0j} = 1,$ $\quad \forall r \in \{1, \dots, p\},$ (1.2)

$\sum_{i=0,i\neq j}^{n} x_{rij} = \sum_{i=0}^{n} x_{rji},$ $\quad \forall j \in \{0, \dots, n\}, r \in \{1, \dots, p\},$ (1.3)

$\sum_{i=0}^{n}\sum_{j=1,i\neq j}^{n} D_j . x_{rij} \leq Q,$ $\quad \forall r \in \{1, \dots, p\},$ (1.4)

$\sum_{r=1}^{p}\sum_{i\in S}\sum_{j\in S,i\neq j} x_{rij} \leq |S| - 1,$ $\quad \forall S \subseteq \{1, \dots, n\},$ (1.5)

$\sum_{i=0}^{n}\sum_{j=1,i\neq j}^{n} d_{ij} . x_{rij} \leq Br_{van},$ $\quad \forall r \in \{1, \dots, p\},$ (1.6)

$x_{rij} \in \{0,1\},$ $\quad \forall r \in \{1, \dots, p\}, i, j \in \{0, \dots, n\}, i \neq j,$ (1.7)

The objective function (1) represents the daily total logistics costs, which is a summation of two cost components. The first cost component represents the total daily fixed costs associated with diesel or electric van fleet, and the second cost component entails the total variable transportation costs. The model constraints (1.1) ensures that each customer point is visited only once. Constraints (1.2) and (1.3) are both flow constraints where (1.2) ensures that all vehicles begin their routes from the depot, while (1.3) ensures that the number of vehicles leaving and arriving at the depot is the same. Capacity constraint (1.4) ensures that the delivery van's payload capacities are not exceeded in their routes. Constraint (1.5) is a sub tour elimination constraint. Constraint (1.6) is only applicable for network alt 2 as it constricts the distance traveled by an electric delivery van to its battery range limit. Finally, constraint (1.7) is a binary constraint for variables.

3.4.1.4 CVRP model implementation procedure

A python algorithm was previously developed for solving the above model on Local solver (LocalSolver: CVRP). This algorithm is used in the proposed DST for network alt 1 and 2 because it allows for the simplification of sub tour elimination constraints in the above CVRP model. With Local solver, a sequence of customer visits can be defined as a list variable. Multiple list variables, equal to the number of delivery trucks, can be added with a partition constraint to ensure every customer point is included, and all list variables are unique.

Furthermore, Lamda function allows for computing the sum of the customer demands and distance between customers for the list variables.

3.4.1.5 CVRP model solution procedure

Based on the stated operating costs and constraints of delivery vans (refer Section 3.2.2), the model parameter values for CVRP are first derived and subsequently inputted to the above algorithm. Followed by model parameter input, the CVRP model is solved exactly on Local solver for the above-generated demand scenario as input. The optimal fleet size of delivery vans and the corresponding minimized TLC value for network alternatives 1 and 2 are obtained as outputs of solving the CVRP model.

3.4.2 Model 2-approximated 2e-LRP:

Finding the cost-optimal configurations of network alternatives 3 and 4 implies determining the locations, numbers, and sizes of micro hubs and vehicle fleet sizes that will minimize the daily TLC and satisfy the demand scenario in question. All these outputs must be obtained concurrently, as they are interdependent. As discussed in Section 2.3, traditional 2E-LRP models seek to determine the cost-optimal configuration for such networks. However, these models are computationally hard to solve as they are a combination of two NP-hard problems (Facility location problem and Vehicle routing problem). Hence, inspired by the work of Winkenbach (2016), a new CA-based two-step optimization method with daily TLC as the objective function is proposed as a substitute for these traditional 2E-LRP models. The proposed model is henceforth referred to as the approximated 2E-LRP model.

The proposed model reduces the computational complexity by decomposing a single complex optimization problem into two relatively simpler optimization subproblems. These two subproblems are interconnected, meaning the output of one problem serves as input for the second problem. Furthermore, the routing component in the second echelon (deliveries by LEFV) is simplified using a CA model by Figliozzi (2008). Adopting this CA model enables to aggregate, analytically, the distance traveled by LEFVs fleets by assuming customer locations are distributed evenly in an area instead of being distinct points.

The clustering problem is the first subproblem, which aims to create a set of compact customer clusters, Such that every customer point from the demand scenario is encompassed by one cluster. Upon forming these clusters, the distance traveled by LEFVs, total customer demand, and LEFV trips required are determined for each of these disjoint clusters. Next, the location fleet size problem (LFP) involves allocating these parameterized disjoint clusters to a set of prospective micro hub locations and concurrently determine the fleet size of the vehicles in the network. Both allocation and fleet sizing is done in such a way that TLC is minimized and all the defined operating constraints for functional elements are satisfied. In this way, solutions to the LFP gives the cost-optimal configuration of network alternatives 3 and 4. The models used to formulate these two subproblems and their respective solution procedures are explained in the following sections.

3.4.2.1 Clustering model

Based on the models in Olafsson, Li, and Wu (2006), an optimization-based model is proposed for clustering the customer points. In this method, the clustering problem is formulated as an integer programming model, which can be solved by exact methods. Unlike K means clustering methods used by Gao et al. (2016), the proposed model does not require the location of cluster centroids as inputs. For this reason, they provide consistent outputs. However, the value of the cluster numbers must still be inputted exogenously to the model.

The proposed clustering model looks for an ideal set of customers from input to serve as cluster centroids and simultaneously assign every customer points to either one of them. This allocation means that any customer can be assigned to itself if they are chosen as a cluster centroid by the model. Therefore, the customer at the centroid, along with the customers assigned to it, forms one distinct cluster. The number of centroids or clusters is equivalent to the exogenous input to the model. The optimal point is reached when all clusters are compact as possible (distance between customers and centroid), and balanced (the total number of LEFV trips required to serve all clusters is minimum). The model formulation for the clustering model is shown below.

3.4.2.1.1 Model assumptions:

- Any customer point from the input can be selected as cluster centroid.
- The number of customer points selected as centroids depends on the input value for the number of clusters.
- Every customer is assigned to one cluster centroid. A customer can be assigned to itself if its location is selected as a cluster centroid.
- LEFV trips required in a cluster is calculated based on the payload capacity of a LEFV.

3.4.2.1.2 Model notation:

The model is described using the notations summarized in Table 3-5, Table 3-6, and Table 3-7.

Table 3-5: Clustering model sets and indices

$\boldsymbol{V}$	$= \{1 \dots \dots . v\}$: Set of customer points
$\boldsymbol{i}, \boldsymbol{j}$	$\in \boldsymbol{V}$

Table 3-6: Clustering model decision and intermediate variables

$\boldsymbol{P_j}$	Binary decision variable indicating if a customer j is selected as a centroid point
$\boldsymbol{A_{ij}}$	Binary intermediate variable indicates if a customer i is assigned to a centroid point j
$\boldsymbol{N_j}$	Binary decision variable indicating the number of LEFVs trips required to service each cluster j

Table 3-7 Clustering model parameters

$\boldsymbol{n_c}$	Number of clusters
$\boldsymbol{C^d}$	The variable cost of LEFV
$\boldsymbol{C^v}$	The fixed cost of LEFV per trip
$\boldsymbol{Q^{Hub}}$	The storage capacity of micro hub
$\boldsymbol{Q^{LEFV}}$	The payload capacity of LEFV
$\boldsymbol{d_{ij}}$	Distances between customer i and j

3.4.2.1.3 Model formulation:

Minimize:

$$\sum_{j=1}^{v}\sum_{i=1}^{v} d_{ij}.A_{ij}.C^{d} + \sum_{j=1}^{v} N_j.C^{v} \qquad (2)$$

Subject to

$A_{ij} \leq P_j,$	$\forall i.j \in V,$	(2.1)
$\sum_{j=1}^{v} P_j = n_c,$		(2.2)
$\sum_{j=1}^{v} A_{ij} = 1,$	$\forall i \in V,$	(2.3)
$\sum_{i=1}^{v} A_{ij}.D_i \leq Q^{Hub},$	$\forall j \in V,$	(2.4)
$\sum_{i=1}^{v} A_{ij}.D_i \leq N_j * Q^{LEFV},$	$\forall j \in V,$	(2.5)
$A_{ij}, P_j \in [0,1],\ \ N_j \in R,$	$\forall i, j \in V,$	(2.6)

The model aims to form customer clusters by finding the values of variables P_j, A_{ij} and N_j such that the objective function (2) is minimized. This objective function comprises of two cost components, (1) LEFV running costs between cluster centroids to assigned customer points, (2) The fixed cost associated with LEFV. Constraint (2.1) ensures that a customer is allocated to only a centroid customer. Constraint (2.2) ensures that the total number of centroids is equal to the input number of clusters n_c. Constraint (2.3) ensures that every customer is assigned to one centroid. Constraint (2.4) restricts the total demand of a cluster to no exceed beyond the micro hub's capacity. Constraint (2.5) ensures that enough LEFV trips required at each cluster are adequate based on payload capacity. Constraints (2.6) are binary and integer constraints for the variables.

3.4.2.1.4 Parameterization of customer clusters.

The optimal clusters thus obtained from the clustering model is parameterized before inputting them to the following model. Since centroids are unique to a customer cluster, every cluster formed by the above model is represented by their respective centroid j. These cluster centroids are enclosed in a customer subset $C \subseteq V$ with a cardinality n_c. The list of parameters, as shown in .

Table 3-8, is calculated for every cluster $j \in C$. The distance traveled by LEFVs is analytically approximated using the CA model by Figliozzi (2008). To use this approximation model, a minimum area rectangle (MAR) bounding the customer is first created to represent the service area of each cluster. Next, distance traveled by LEFVs is approximated by assuming that the customer points enclosed in a cluster are uniformly distributed within their respective service area(MAR).

Table 3-8: Parameters of a customer cluster.

$\boldsymbol{N_j}$	Number of LEFV trips required to service the customer cluster j
$\boldsymbol{Q_j}$	The total customer demand for cluster j
$\boldsymbol{A_j}$	The area of minimum area rectangle (MAR) bounding all customers in cluster j
$\boldsymbol{Td_j}$	The approximate total distance traveled by N_j LEFVs within the cluster j $= k * \frac{n_j - N_j}{n_j} * \sqrt{n_j.A_j}$ (Value of local tour parameter is provided as input)

3.4.2.1.5 Working of the clustering model

To demonstrate the working of the above clustering model, an example problem instance with nine customers is assumed to be solved by the above clustering model for 2 clusters. The problem and the plausible clustering solution is shown in Figure 3-8 for representation purposes only. It is evident from the output that the model picks customers 2 and 7 as the centroids and groups the other customers around them, such that the obtained clusters are compact and relatively balanced. The latter means that the LEFV trips are not making trips with very fewer packages. After cluster formation, each cluster is parameterized, as shown in Figure 3-9.

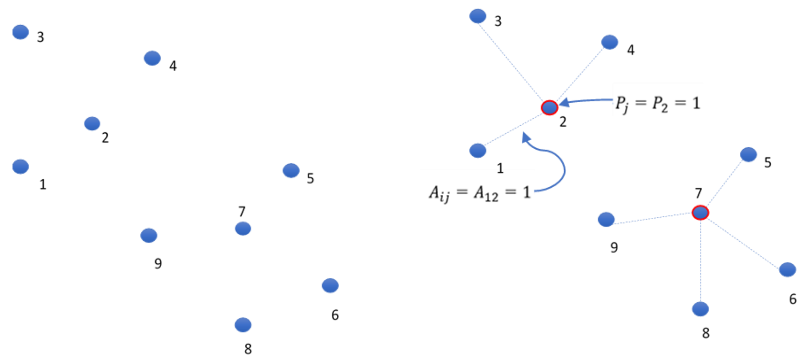


Figure 3-8: Clustering model example input and output

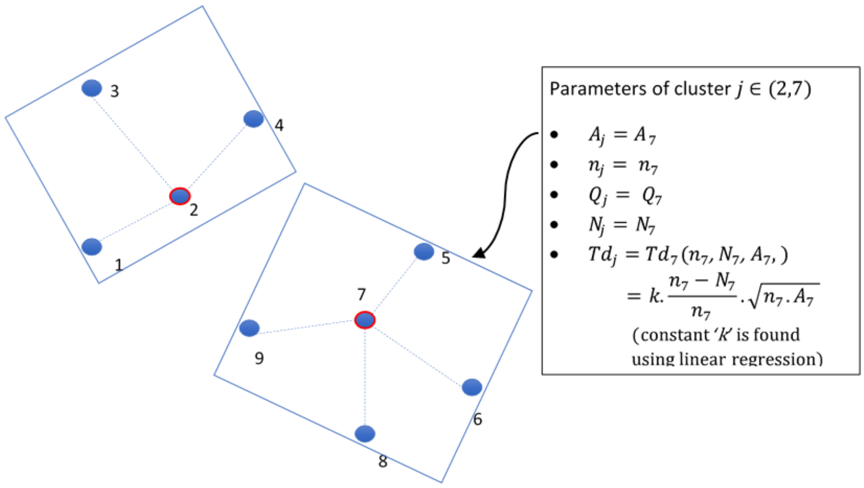


Figure 3-9: Parameterization of customer clusters

3.4.2.2 Location and fleet size model;

With parameterized clusters as inputs, Location and fleet size problem (LFP) must take the following decisions concurrently: (1) select location for a micro hub and its size (2) allocate every parameterized cluster to one of these activated micro hub locations, (3) determine LEFV fleet sizes at each activated micro hub location, (4) determine the routes of trucks in the first echelon. An integer programming model based on the 2E-LRP model of Crainic et al., (2011) and facility location and allocation model of Tragantalerngsak et al. (2000) is proposed to solve the above LFP.

Two sets of binary decision variables are used to indicate which prospective micro hub location needs to be activated and which customer cluster should be allocated to each of these activated micro hub locations. The size of the micro hubs can be obtained by defining multiple prospective micro hub locations with identical coordinates. In this way, a larger micro hub can be represented by multiple identical hubs being activated at the same place. Additionally, another set of integer variables is used to denotes the fleet size of LEFVs required at each micro hub. For simplicity, the value of these variables is aggregated as the quotient of total distance traveled by the LEFVs from micro hubs (in allocated clusters) and the driving range of LEFVs. Moreover, the proposed model also determines the optimal routes of the box trucks in the first echelon using another set of binary decision variables.

3.4.2.2.1 Model Assumptions:

The following assumption are underlying in the proposed model:

- All micro hubs are homogeneous and have limited capacity.
- The problem is static (demand of customers is deterministic).
- All LEFV travel equal to their driving range limit.
- The LEFV and box truck fleets are homogenous and capacitated.
- The model has a single objective function minimizing the daily TLC.
- No time windows included are included in the model.
- The LEFVs are charged overnight at the micro hubs.

3.4.2.2.2 Model Notation:

The model is described using the notation summarised in Table 3-9, Table 3-10 and Table 3-11

Table 3-9: LFP model sets and indices

$\boldsymbol{C}$	Set of clusters obtained as outputs from the clustering model
$\boldsymbol{V}$	$=\{0,1 \dots \dots . v\}$: index set of prospective micro hub locations where micro hub location at indexed at 0 denotes depot location.
$\boldsymbol{P}$	$=\{1 \dots \dots . p\}$: index set of homogeneous box trucks
$\boldsymbol{j}$	$\subseteq \boldsymbol{C}$
$\boldsymbol{h}, \boldsymbol{l}$	$\subseteq \boldsymbol{V}$
$\boldsymbol{k}$	$\subseteq \boldsymbol{P}$

Table 3-10: LFP model Decision and intermediate variables

$\boldsymbol{W_h}$	Binary decision variable denotes if a micro hub h is activated
$\boldsymbol{X_{jh}}$	Binary intermediate variable denotes if a cluster j is assigned to a micro hub location h
$\boldsymbol{M_h}$	Integer decision variable denoting LEFV fleet size at micro hub location h
$\boldsymbol{Z_{khl}}$	Binary decision variable denoting if a box truck k is used to move bundled packages between micro hubs h and l , where $h \neq l$
$\boldsymbol{D_h}$	Integer intermediate variable denoting total distance travelled by M_h LEFVs from micro hub h to serve all clusters assigned to it
$\boldsymbol{Q_h^{hub}}$	Integer intermediate variable denoting the total demand of all customers assigned to micro hub h

Table 3-11: LFP model parameters

F^h	The operating cost of a micro hub per day
C^{LEV}	The fixed cost of LEFV per day
C^d	The variable cost of LEFV
C^T	The utilization cost of the box truck (diesel /electric)
D_{hl}	The distance between hubs h and l
d_{jh}	The distance between centroid point of cluster j and micro hub h
Br_{LEV}	The battery range of LEFV
Q^{Hub}	The capacity of the micro hub
Q^1	The payload capacity of the box truck (diesel /electric)
Td_j	LEFV travel distances within customer cluster j from clustering model
N_j	Number of LEFV trips required for each cluster j from clustering model
Q_j	The Customer demand for cluster j from clustering model

3.4.2.2.3 Model formulation:

Minimize:

$$\underbrace{\sum_{h=1}^{v} W_h . F^h}_{\text{Total daily fixed cost of micro hubs}} + \underbrace{\sum_{h=1}^{v} C^{LEV} . M_h}_{\text{Total daily fixed cost of LEFV}} + \underbrace{\sum_{h=1}^{v} C^d . D_h}_{\text{Total variable transport cost of LEFV}} + \underbrace{\sum_{k=1}^{p} \sum_{h=0}^{v} \sum_{l=0\, h\neq l}^{v} C^T . D_{hl} . Z_{khl}}_{\text{Total utilization cost of box trucks (costs for visiting activated \& deactivated micro hubs)}} - \underbrace{\sum_{l=1}^{v} C^T . 2 . D_{0l} . |W_l - 1|}_{\text{Box truck utilization costs for visiting only deactivated micro hubs}} \qquad (3.1)$$

Subject to

- $X_{jh} \leq W_h \qquad \forall j \in C, h \in V \setminus \{0\} \qquad (3.2)$
- $\sum_{h=1}^{v} X_{jh} = 1 \qquad \forall j \in C \qquad (3.3)$
- $D_h = \sum_{j\in C} X_{jh} . [\, Td_j + 2(\, d_{jh} . N_j) \,] \qquad \forall h \in V \setminus \{0\} \qquad (3.4)$
- $M_h . Br_{LEV} \geq D_h \qquad \forall h \in V \setminus \{0\} \qquad (3.5)$
- $Q_h^{hub} = \sum_{j\in C} X_{jh} . Q_j \qquad \forall h \in V \setminus \{0\} \qquad (3.6)$
- $Q_h^{hub} \leq Q^{hub} \qquad \forall h \in V \setminus \{0\} \qquad (3.7)$
- $\sum_{k=1}^{p} \sum_{h=0\, h\neq l}^{v} Z_{khl} = 1 \qquad \forall l \in V \setminus \{0\} \qquad (3.8)$
- $Z_{khl} \leq W_l \qquad \forall h, l \in V \setminus \{0\}, h \neq l, k \in P \qquad (3.9)$
- $\sum_{l=1}^{v} Z_{k0l} = 1 \qquad \forall k \in P \qquad (3.10)$
- $\sum_{h=0\, h\neq l}^{u} Z_{khl} = \sum_{h=0\, h\neq l}^{u} Z_{klh} \qquad \forall l \in V, k \in P \qquad (3.11)$
- $\sum_{h=0}^{u} \sum_{l=1\, h\neq l}^{u} Q_l^{hub} . Z_{khl} \leq Q^1 \qquad \forall k \in P \qquad (3.12)$
- $\sum_{k=1}^{p} \sum_{h\in S} \sum_{l\in S\, h\neq l} Z_{khl} \leq |S| - 1 \qquad \forall S \subseteq V \setminus \{0\} \qquad (3.13)$

The objective function (3.1) represents that daily TLC. It comprises of three main cost components, the total daily fixed operating cost of micro hubs, total daily fixed and variable cost of LEFVs, and total utilization cost of box trucks in the first echelon of goods transport. For finding the total utilization costs of box trucks, the costs of unnecessary visits to deactivated micro hubs by the additional box trucks are invalidated. This approach is adopted to avoid nonlinear constraints and objective functions. Constraint (3.2) ensures that a customer cluster j is assigned to micro hub location h (X_{jh}=1) only if micro hub location h is activated ($W_h = 1$). Constraint (3.3) makes sure that every cluster is assigned to only one micro hub location. Constraints (3.4) and (3.5) ensures that, for each micro hub h, the total battery range of M_h number of LEFVs is at the least equal to the total distance required to service customer clusters assigned it. Constraints (3.6) and (3.7) ensures the storage capacities of micro hubs are not violated. Constraint (3.8) is a flow constraint in the first echelon, which ensures that every micro hub (activated /deactivated) is visited by a box truck form either the depot or another micro hub. Constraints (3.9) will ensure that the box truck can serve multiple micro hubs on a trip only if they are activated. Constraints (3.10) ensures that every truck k starts its trip from the depot. Constraint (3.11) guarantees that the number of box trucks arriving is equal to those leaving at every micro hub and depot. In this way, Constraints 3.8, 3.9, 3.10, and 3.11 make sure that the activated micro hubs are visited by a vehicle either from the depot or another activated micro hub whereas, deactivated micro hubs are visited by individual box truck from the depot. The costs of these dedicated routes to deactivated micro hubs from the depot are deducted from the total utilization cost of box trucks, as seen in the objective function. In this way, only the costs of utilizing box trucks for activated micro hubs are considered in TLC computation. Constraint (3.12) makes sure that the payload capacity of box trucks is not violated, and constraint (3.13) is a sub route elimination constraint for the first echelon.

3.4.2.2.4 Solution procedure.

To model the proposed approximate 2E-LRP corresponding to alternatives 3 and 4, the clustering problem and LFP for these two network alternatives are individually modeled using the above two formulations. The values for their model parameter are either assumed (for the number of customer clusters n_c) or derived based on the defined operating costs and constraints of functional elements (for LEFVs, micro hubs, and box trucks). Upon inputting these parameter values to their respective models, both these models are solved exactly but in a sequential manner. Firstly the clustering problem is solved using demand scenarios as input. Later, using outputs of the cluster model as inputs, the LFP model is solved to give the cost-optimal configurations and corresponding minimum TLCs for network alternatives 3 and 4. However, due to this sequential flow of data between the models, the value for the parameter n_c inputted exogenously into the clustering model indirectly influences the outputs obtained from solving the LFP model. Simply put, the minimized TLC value and the corresponding cost-optimal network configurations obtained by solving the LFP model varies with the value of n_c inputted into the clustering model. Therefore, it is possible that by changing the value of n_c, the minimum TLC can drop further and yield a better cost-optimal configuration.

To take into account of this relationship, it is imperative to find ideal input values of the parameter n_c from all its possible values to identify the best cost-optimal configuration that results in the lowest minimum TLC value. For this reason, a solution algorithm (as illustrated in Figure 3-10) is built to iteratively solve the above models (in the sequential order) for a range of input values of n_c. At the end of every iteration, the minimized TLC values obtained are plotted against input cluster number n_c. After all iterations of the solver algorithm are completed, the input value of n_c which induced the lowest minimum TLC value is identified from this minimum TLC vs n_c plot. The cost-optimal network configuration corresponding to this lowest minimum TLC value is recognized as the best cost-optimal configuration of the network, and the solution for the overall approximated 2E-LRP. This proposed solution method is a heuristic approach adopted instead of a complex bilevel optimization problem. Although the global optimum solution may not be found, a local optimum with a feasible network configuration can be determined with this approach.

Since the range of input values of n_c is the equal to the number of customer points in the demand scenario, a large number of iterations can be carried out to explore all possible value of n_c before finding the best cost-optimal configuration. Consequently, the computational times will increase beyond reasonable levels, especially for realistic demand scenarios (>200 customers). Thus, the number of iterations can be reduced by narrowing down the range of input values of n_c. Small values of n_c result in big customer clusters having a total demand more than the capacity of micro hubs is infeasible. Therefore, the values of the lower limit of n_c (n_{min}) is calculated within the algorithm as the ratio between the number of customers in demand scenario to micro hub's storage capacity. On the other hand, large values of n_c results in small clusters that have a total customer demand less than LEFV payload capacities, resulting in underutilized LEFVs and concomitant increase in TLC. Hence, the value of the max limit of n_c denoted by n_{max} must be predetermined based on the number of customers within the demand scenario and payload capacity of LEFVs utilized.

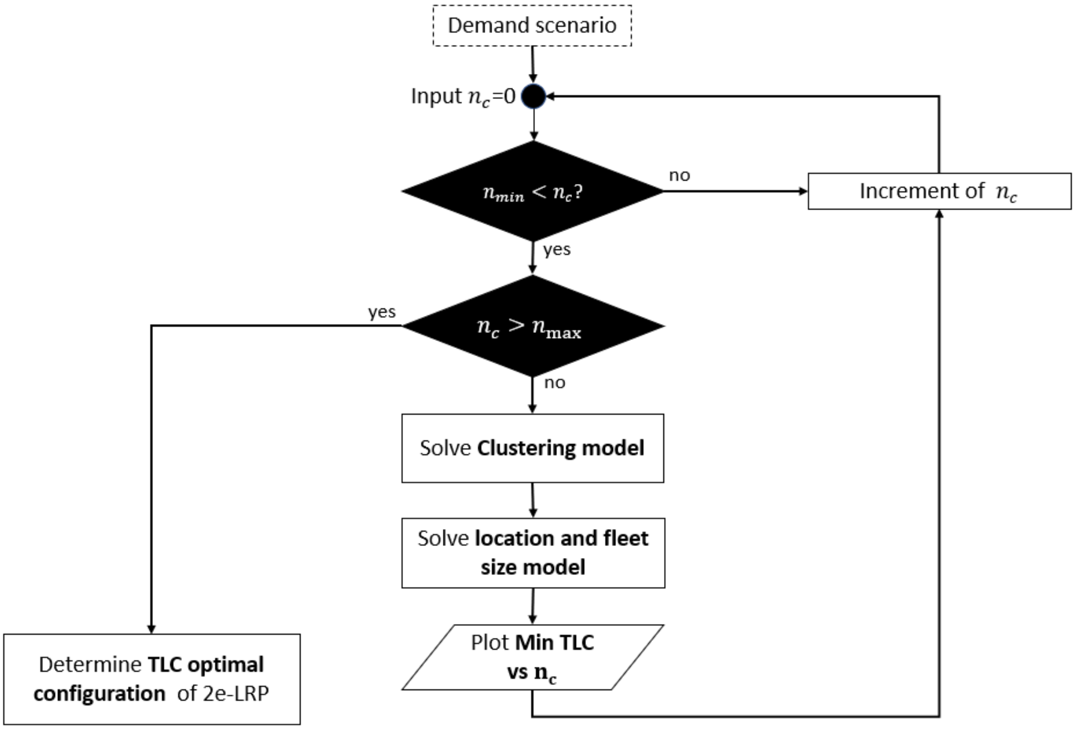


Figure 3-10: Sequential iterative solution algorithm for approximated 2E-LR

3.5 NETWORK PERFORMANCE COMPARISON

The final step in the DST involves measuring and comparing the performance of network alternatives with each other using the thus obtained cost-optimal configurations. This step is crucial as it provides the required insights for changing from the current network to an urban transshipment network. The performance is measured using three broad categories of KPIs, namely economic, environmental, and operational KPIs. All the individual KPIs from these categories are elucidated in the following sections.

3.5.1 Economic Performance:

From an economic point of view, two KPIs are analyzed, *daily TLC* and the *average cost per unit.* The *daily total logistics cost* of a network alternative is equivalent to the minimum TLC corresponding to the cost-optimal configuration of networks. Whereas, the *average cost per unit* is estimated using the below formulae.

- $\boldsymbol{The\ average\ cost\ per\ unit} = \frac{daily\ total\ logistics\ cost\ (TLC\ )}{number\ of\ parcels\ delivered}$

3.5.2 Environmental Performance:

From an environmental perspective, network alternatives are compared based on the *total Well-to- Wheel (WTW) CO_2 emissions* from freight vehicles. This KPI involves two sub-components, Well-to-Tank (WTT), and Tank- to-wheel (TTW) emissions. The former accounts for the CO_2 emissions discharged during the production of fuel or electricity, whereas the latter includes tailpipe discharge from vehicle fleets. The following set of formulas are used to measure the value of *total WTW CO_2 emissions:*

- $$\boldsymbol{Total\,WTW\ CO_2\ emissions} = Total\ WTT\ CO_2\ emissions\ all\ vehicles\ modes + Total\ TTW\ CO_2\ emissions\ all\ vehicles\ modes$$

Where,

- $$WTT\ CO_2\ emissions\ per\ vehicle\ mode = Total\ distances\ traveled\ per\ vehicle\ mode \times Vehicle's\ energy\ consumption\ \times CO2\ emissions\ per\ litre\ of\ diesel\ or\ kWh\ of\ electricity\ produced$$

- $$TTW\ CO_2\ emissions\ per\ vehicle\ mode = \ Distances\ traveled\ per\ vehicle\ mode \times Vehicle's\ energy\ consumption\ \times CO2\ emissions\ per\ liter\ of\ diesel\ or\ kWh\ of\ electricity\ consumed$$

For the above formulas, *Total distance traveled per vehicle mode* is obtained as outputs from network optimization models. Values for *vehicles' energy consumption* is equivalent to fuel or energy consumption of diesel and electric vehicles used in network alternatives (from defined vehicle specifications). Whereas, the average values for *CO_2 emissions per liter of diesel and kWh of electricity produced* or *consumed* must be inputted exogenously by the LSP.

Additionally, from an environmental perspective, It is essential to check if an LSP would consider shifting from the conventional network alternatives with diesel vehicles to sustainable network alternatives with electric vehicles. Therefore, a new qualitative KPI called the *likelihood of adoption* is defined to predict the chances of an LSP to adopt network alternatives 2, 3, and 4 from network alt 1. Considering that network alt 1 is the current network that uses diesel vans in LEZ, the *likelihood of adoption* is measured explicitly for network alt 2, 3, and 4, which employ either LEFVs or electric box trucks. This KPI is measured based on two parameters, minimum LEZ penalty on diesel vans to shift from alternative 1 (MPDS) and the actual LEZ penalty as levied by the municipality.MPDS is determined using the outputs of the network optimization models, whereas actual LEZ is exogenously inputted based on the context. The formulas used to calculate the parameters and the KPI are shown below.

- $\textbf{Likelihood of adoption} = \mathrm{HIGH}$, if MPDS < actual LEZ penalty

  Or

  LOW, if MPDS > actual LEZ penalty

  Where,

- $MPDS = \frac{Daily\ TLC - Daily\ TLC\ of\ network\ alt\ 1}{The\ optimal\ fleet\ size\ of\ diesel\ vans\ for\ network\ alt\ 1}$

The values for *Daily TLC* and *optimal fleet sizes of diesel vans for network alt 1* are obtained from the outputs of network optimization models. Whereas, the actual *LEZ penalty* is as an input parameter.

3.5.3 Operational Performance:

Considering that time is very crucial in last-mile deliveries to LSP's financial resources and customer satisfaction, two KPIs, namely *total operation time* and *average service time per customer*, are measured for network alternatives. Measuring these KPIs shows if a network requires more or reduced time to perform deliveries to customer locations compared to other network alternatives.

- $\boldsymbol{Total\ Operation\ time} = Total\ travel\ time\ all\ vehicle\ modes + Total\ handling\ time\ all\ vehicle\ modes$

  Where,

- $Travel\ time\ per\ vehicle\ mode = \frac{Distance\ traveled\ per\ vehicle\ mode}{average\ speed}$

- $Handling\ time\ per\ vehicle\ mode = Total\ delivery\ time\ at\ customer\ reception\ points + Handling\ time\ at\ micro\ hubs\ (LEFV\ or\ box\ trucks)$

- $\textbf{Average service time per customer} = \frac{Total\ operation\ time\ per\ day}{Number\ of\ customers\ per\ day}$

For the above formulas, *Distances traveled by the vehicles* are obtained as outputs from network optimization models. Whereas, the values of the *average speed of vehicles, delivery time per customer,* and *handling time at micro hubs* for LEFVs or box trucks are exogenously specified based on the information collected from existing operations.

4 Application:

The proposed DST is applied to a synthetic case in this chapter. The complete case is not described in this research. Instead, the sources of internal and external information required from the case for every process of the DST (see Figure 3-1) is derived from an array of external information sources. The description of the information sources and their application in the DST is explained in the following sections

4.1 Generation of demand scenarios:

Demand scenarios are generated using VRP benchmark instances previously proposed by OR scholars to mimic the service needs of an LSP on a typical weekday. These problem instances are used because they are designed to provide a balanced experimental setting for benchmarking the performance of VRP solution algorithms. Recently, Uchoa et al. (2017) created a set of problem instances containing a realistic distribution of points of deliveries (POD) for testing CVRP solution algorithms. From this set, three problem instances with 260, 500, and 950 PODs are specially selected, such that the density of PODs linearly increases across the instances. Meaning that the area in which PODs are enclosed remains the same, but the number of customer points increases nearly doubles (=1.9) across instances. Three different demand scenarios are created by representing every POD in these instances as individual customer points (schematized in Figure 4-1). The reason behind choosing these demand scenarios in this study is to analyze how the performance of network alternatives change as the customer density within LEZ changes.

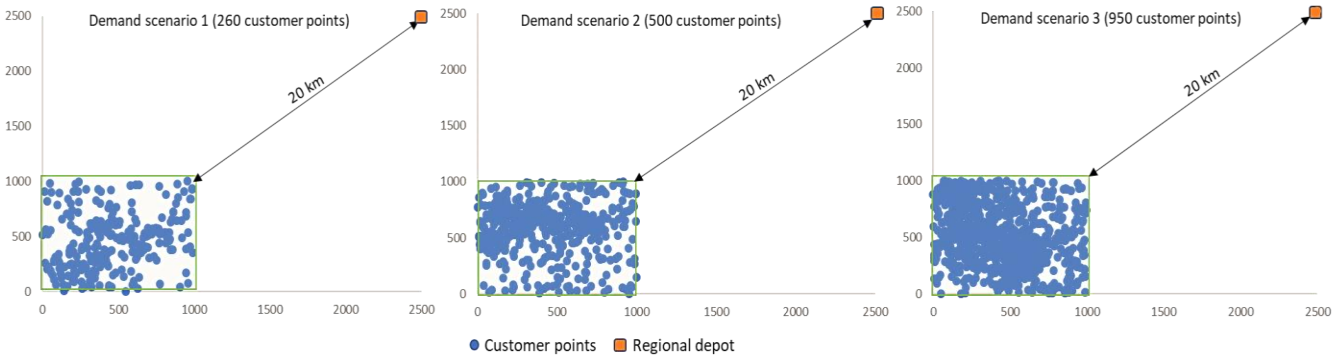


Figure 4-1: Generated demand scenarios

The additional assumptions that are considered in the above demand scenarios are listed below;

- The service is limited only to package delivery.
- Each customer point has a demand for one package. All parcels are assumed to be of the size *42L*. The value is based on the average package size considered in Lee et al. (2019a).
- The demands of all customers in the scenario are assumed to be fulfilled within one operational day.
- The travel distance between any two points in the scenarios is measured in the Euclidian distance metric with each metric equivalent to 10 meters. This value is based on the estimated average distance per parcel in Clarke & Leonardi (2017).
- A virtual square area encompassing all customer points is used to represent the LEZ in all three demand scenarios, as shown in Figure 4-1. The lengths of the square LEZ area are set as *10km* and retained the same across all three demand scenarios.

- The location of the depot is fixed at 20km distance from the boundary of LEZ in all three scenarios. This length is based on the average distances between the depot and the first delivery stop in case studies used by Clarke & Leonardi (2017).

4.2 PROSPECTIVE MICRO HUB LOCATIONS IN DEMAND SCENARIO:

For network alternative types 3 and 4, prospective locations where micro hubs can be established must be specified alongside customer points in the demand scenario. From these locations, the proposed solver algorithm then activates the locations of the micro hubs. Six arbitrary sites on the periphery of the LEZ are selected to serve as prospective micro hub locations for alternative type 3. These potential hub locations are retained the same across all demand scenario. On the other hand, the six random sites from dense regions are selected as prospective hub locations for network type 4. The potential sites of alternative 4 are unique to each demand scenario. The prospective hub locations for both alternatives 3 and 4 in each demand scenario are shown in Figure 4-2.

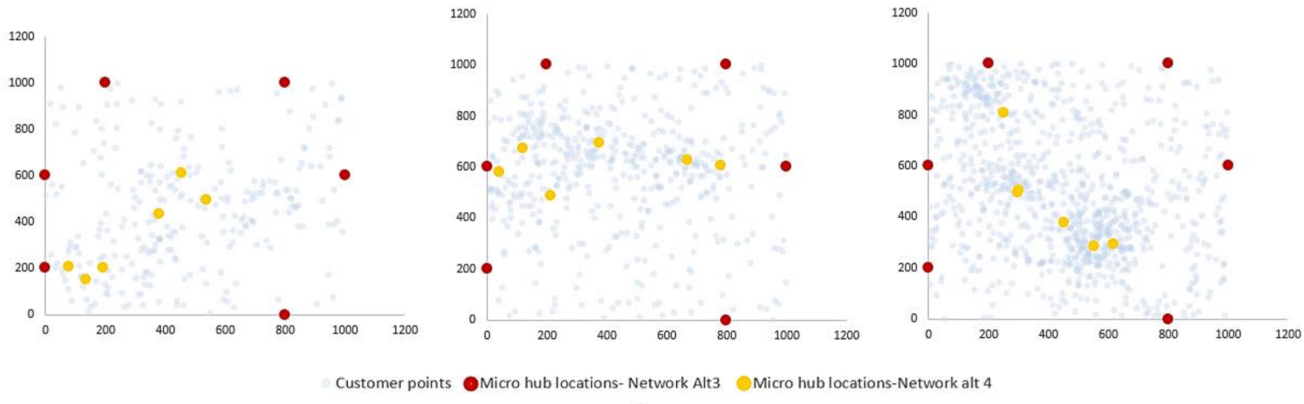


Figure 4-2:Prospective micro hub locations in demand scenarios

4.3 DEFINE OPERATING COSTS AND CONSTRAINTS OF FUNCTIONAL COMPONENTS

To simulate realistic logistic network alternatives, the cargo vehicle variants analyzed within the Panteia's total cost of ownership (TCO) model are selected for application within the network alternatives. The prices and specifications of these vehicles are extracted from the information database of the TCO model (refer appendix A). The operating costs and constraints are derived using the information, calculation procedures, and parameters available in this TCO model. Furthermore, the information relevant to micro hubs is obtained based on the results of the LEFV-LOGIC project (Ploos Van Amstel et al., 2018). All the derived values for the operating costs and specifications, along with the calculation procedures, are explained in Table 4-1.

Application:

Table 4-1 Operating costs and specifications of network elements

Network components	Costs and specifications of network elements	Calculation procedures
Diesel vans (for alt 1)	• Daily depreciation cost **= 9.64 €** • Daily labour costs/vehicle**= 120 €** • Running cost of the vehicle **=0.18 €/km** • The cargo capacity of the vehicle **= 4200 L**	• <u>The daily depreciation cost of a vehicle is calculated as</u> ***{Acquisition costs - Resale price} / {ownership period * No. of working days in a year}*** Assuming, - No. of working days in a year =**260 days** - Ownership period of vehicles = **8 years** - *Acquisition costs of vehicle= {Purchasing price + insurance cost and road tax for the ownership period}* - Resale price of the vehicle (end of 8 years) = **19% of the purchasing price** • <u>The daily labour costs are given by:</u> ***Hourly wage of vehicle operator * working hours/day*** Assuming, - Hourly wages of delivery van operator =**15 €** - Hourly wages of LEFV operator=**12€** - Working hours/day for delivery van = **8 hours** - Working hours/day for LEFV= **6 hours** • <u>The running cost of vehicle is given by:</u> ***{Vehicle mileage* Energy price} + Maintenance cost*** Assuming, - Energy price for all diesel-powered vehicles
Battery electric vans (for alt 2)	• Daily depreciation cost **= 17.44€** • Daily labour costs/vehicle**= 120 €** • Running cost of the vehicle = **0.08 €** • The cargo capacity of the vehicle **= 4200 L** • Driving range **= 145 km**	
LEFV (for both alt 3 and 4)	• Daily depreciation cost **= 4.26 €** • Daily Labour costs/vehicle**= 72 €** • Running cost of the LEFV **= 0.02 €/km** • The cargo capacity of the vehicle **= 850 L** • Driving range **= 70 km**	

<table>
<tr>
<td>Diesel box trucks
(for alt 3)</td>
<td>▪ Utilization cost = 0.87 €/km

▪ The cargo capacity = 10800 L</td>
<td rowspan="2">= 1.3 €/L (diesel price)
- Energy price of electric vehicles include electricity price and a surcharge for charging infrastructure
▪ Energy price of electric van/truck = 0.45 €/kWh (20kw charging)
▪ Energy price of LEFV= 0.22 €/kWh
(3kw charging)

• <u>The utilization cost of a box truck is calculated as</u>

{Daily depreciation cost of box truck / average distance travelled} + the running cost of box truck + service cost

Assuming,
- Service cost = {Hourly wage of box truck operator * Average speed of box trucks}
- The average distance travelled by box truck = 50 km
- Hourly wages of box truck operator= 15 €
- The average speed of box truck = 40 km/h</td>
</tr>
<tr>
<td>Electric box trucks
(for alt 4)</td>
<td>▪ Utilization cost = 1.09 €/km

▪ The cargo capacity = 10800 L</td>
</tr>
<tr>
<td>Micro hub
(for both alt 3 and 4)</td>
<td>▪ The daily operating cost of the micro hub (€) = 115 euros

▪ The storage capacity of micro hub =8500 L</td>
<td>• <u>The daily operating cost of the micro hub is given by</u>:
The yearly cost of micro hub / No. of working days in a year
Assuming,
- The yearly cost of micro hub = 30000 € (incl. rent and staff)
- No. of working days in a year =260 days</td>
</tr>
</table>

4.4 MODEL PARAMETER VALUES:

For modeling the CVRP or approximated 2E-LRP corresponding to network alternatives, the values of the model parameters are estimated based on the above-defined operating costs and constraints of network elements(refer Table 4-1). Since both network alternatives, 1 and 2 are modeled into a CVRP model, values of their corresponding model parameters are listed together in Table 4-2. Parameter values for modeling approximated 2E-LRP model (clustering model and cluster allocation models) corresponding to network alternatives 3 and 4 are listed in Table 4-3. Furthermore, assumptions made for deriving model parameter values from operating costs and specifications of functional elements are specified for every model parameter. It should be noted that in the above models, all cargo vehicles and micro hubs are considered to be capacitated based on the volume of the package. The reason is that the size to weight ratio of the parcels in last-mile deliveries is usually considerably large (Lee et al., 2019a).

Table 4-2:CVRP model parameters input values

Model parameters	**Network alt 1** (diesel vans)	**Network alt 2** (battery-electric vans)	**Assumptions**
The fixed cost of the van per day (€) - $\boldsymbol{C}$	129.64	137.44	= Daily depreciation cost + Daily labour costs/vehicle
The variable cost of a van (€/km)- $\boldsymbol{c}$	0.18	0.08	= Running cost of the vehicle
The payload capacity of the van (packages)- $\boldsymbol{Q}$	100	100	= The cargo capacity of the vehicle/ size of a package (42 L)
Battery range limit of the electric van (km)- $\boldsymbol{Br_{van}}$	N/A	145	= Driving range of a vehicle
Distances between customer i and j - $\boldsymbol{d_{ij}}$	{Euclidean metric} * 10 meters		Based on the defined demand scenario

Table 4-3: Approximated 2E-LRP model parameters

Model parameters	**Network Alt 3** (LEFV+ micro-hubs+ diesel box trucks)	**Network Alt 4** (LEFV + micro-hubs+ electric box trucks)	**Assumption**
The variable cost of LEFV (€/km) -$\boldsymbol{C^d}$	0.02	0.02	= Running cost of LEFV
Fixed cost of a LEFV per trip - $\boldsymbol{C^V}$	76.26	76.26	= Daily depreciation cost of LEFV + Daily labour costs/LEFV
The capacity of a micro hub- $\boldsymbol{Q^{Hub}}$	200	200	= The storage capacity of the micro hub/ size of a package (42 L)
The payload capacity of LEFV- $\boldsymbol{Q^{LEFV}}$	20	20	= The cargo capacity of the vehicle/ size of a package (42 L)
The operating cost of a micro hub per day (€)- $\boldsymbol{F^h}$	115	115	= The daily operating cost of the micro hub
The fixed cost of LEFV per day (€/km)- $\boldsymbol{C^{LEV}}$	76.26	76.26	=Daily depreciation cost of LEFV + Daily labour costs/LEFV

The utilization cost of the box truck (€/km)-$\boldsymbol{C^T}$	0.87	1.09	= Utilization cost of box trucks
Battery range of LEFV (km)- $\boldsymbol{Br_{LEV}}$	70	70	= the driving range of a LEFV
The payload capacity of box truck (packages)-$\boldsymbol{Q^1}$	250	250	= The cargo capacity of the vehicle/ size of a package (42 L)
Distances between hubs h and l (km)-$\boldsymbol{D_{hl}}$	{Euclidean metric} * 10 meters		Based on the assumption in the defined demand scenario (refer Section 4.1)
Distances between cluster centroid j and micro hub h (km)- $\boldsymbol{D_{jh}}$			
Distances between customer i and j - $\boldsymbol{d_{ij}}$			
Travel distances within customer cluster j (km)-$\boldsymbol{Td_j}$	Outputs from the clustering model		Based on the sequential flow of data in the approximated 2e-LRP model (refer section 3.4.2.2.4)
Number of LEFV trips required for each cluster j- $\boldsymbol{N_j}$			
The Customer demand for cluster j- $\boldsymbol{Q_j}$			

4.4.1 Specify the value of local tour parameter K in the CA model:

CA-based model is utilized in the proposed approximate 2E-LRP to estimate the total distance traveled by LEFVs tours within a cluster. Like shown earlier in Section 3.4.2.1.4, The CA model used in the approximate 2e-LRP model has the following terms:

- local tour parameter k
- Total distance approximation formulae $\frac{n-N}{n}.\sqrt{n*A}$

To solve the proposed approximate 2e-LRP model, the value of the local tour parameter k for the CA model must be specified as an input. However, the value of k is contingent on the spatial distribution of customer points in the demand scenario. Therefore, its value must be derived through linear regression for each of the above-generated demand scenarios.

Regression analysis is performed by setting the total distance approximation term as a single explanatory variable, and the exact total distance traveled as the dependent variable. In every demand scenario, a collection of circular areas are created with the random customer as centers and with varying radius. For the customer pints within each of these circles, exact distances traveled by LEFVs originating from the center is determined. This exact distance is determined by formulating a CVRP for each of these circles and solving it exactly. In parallel, The approximate distance traveled by LEFV within these circles is determined using the CA model. The relationship between these two variables is analyzed by fitting a linear model to these observed set of values for travel distances. The intercept is considered zero as all LEFVs start trips from the center. Concurrently, the value of local tour parameter K can be obtained as the coefficient values. The values of K determined for each scenario are tabulated for the demand scenarios, as shown below in Table 4-4.

Table 4-4: Local tour parameter values

Demand scenario	Value of '*K*'
Demand scenario 1 -260	2.4
Demand scenario 2 -500	2.5
Demand scenario 3 -950	2.45

4.4.2 Specify the maximum limits of the iterative solver algorithm n_{max}

As discussed in Section 3.4.2.2.4, the upper limits to the input number of cluster of n_c must be defined to limit the number of iteration in the solver algorithm. We consider the value of n_{max} equal to the ratio of the number of customers in the demand scenario 3 to half of LEFV's payload capacity. The reason is that demand scenario 3 has the largest number of customer points. Considering that LEFV can hold 20 packages and demand scenario 3 has 950 customers, the value of n_{max} is equal to 95. This value of n_{max} is kept the same across all three demand scenarios.

4.4.3 Model implementation

The CVRP model, as mentioned in SCVRP model implementation procedure 3.4.1.4, is implemented in Python 3.8 and solved using Local solver. On the other hand, the approximated 2E-LRP model and the iterative solution algorithm is implemented in Python 3.8 and solved using GUROBI. The implementation of both these models is carried on a 1.8 GHz Intel Core i5 processor with 8 GB RAM.

4.5 NETWORK PERFORMANCE COMPARISON

As seen in Section 3.5, the measurement of environmental, operational KPIs requires few parameters values that should be defined by LSPs exogenously based on their business context. For the synthetic case study, these values have been assumed using relevant sources of information, as listed in Table 4-5.

Table 4-5:Parameters for KPI calculation

KPI category	Parameter for KPI measurement	Values (sources of information)
Environmental performance	$CO2\ emissions\ per\ litre\ of\ diesel\ or\ kWh\ of\ electricity\ produced$	• **0.617 kg/litre** (based on the energy conversion factor in BEIS, 2019) • **0.616 kg/kWh** (**F**or electric vehicles based on average EU mix in European Association for Battery Electric Vehicles,2009)
	$CO2\ emissions\ per\ liter\ of\ diesel\ or\ kWh\ of\ electricity\ consumed$	• **2.67 kg/l** (For diesel vehicles based on Soares, 2012) • **0 kg/kWh** (For electric vehicles no tailpipe emissions)
	$Actual\ LEZ\ penalty$	**95 €** based on the average penalties stated by Dablanc & Montenon, (2015)

Operational Performance	*Average vehicle speed*	▪ Diesel/Electric vans– **18 Km/h** (Balm et al., 2018) ▪ LEFV – **12.5 km/h** (Balm et al., 2018) ▪ Diesel /electric Box trucks– **38 km/h** (Panteia TCO model)
	Time at customer reception	**2 mins** (Ballare & Lin, 2020)
	Handling time at micro hubs	• Handling time LEFV- **10 min** (self-assumption) • Handling time Box truck- **30 min** (Ballare & Lin, 2020)

5 RESULTS AND INTERPRETATION:

In this chapter, the evaluation of the case study results is performed. The outputs from the network optimization models are presented and discussed individually, followed by the validation of the approximation techniques employed within the proposed optimization model. Lastly, the performance comparison of network alternatives is discussed.

5.1 NETWORK OPTIMIZATION RESULTS

In this section, the outputs obtained from the CVRP and the approximated 2E-LRP models are discussed. Furthermore, outputs from the two sub-models within the approximated 2E-LRP are also presented and discussed.

5.1.1 Solutions of CVRPs

Figure 5-1 shows the cost-optimal fleet sizes of delivery vans (diesel and electric) used in network alt 1 and 2 as obtained by solving their respective CVRPs for three different scenarios. It appears that the network alt 2 requires one additional vehicle for fulfilling all demand scenarios when compared with network alt 1. This difference is primarily due to the limited driving range constraints of battery-electric vans in network alt 2. Furthermore, the TLC corresponding to the cost-optimal fleet size of network alt 1 and 2 are indicated in Table 5-1. Due to the additional vehicles required in the fleet, TLC of network alt 2 increases compared to that of network alt 1.

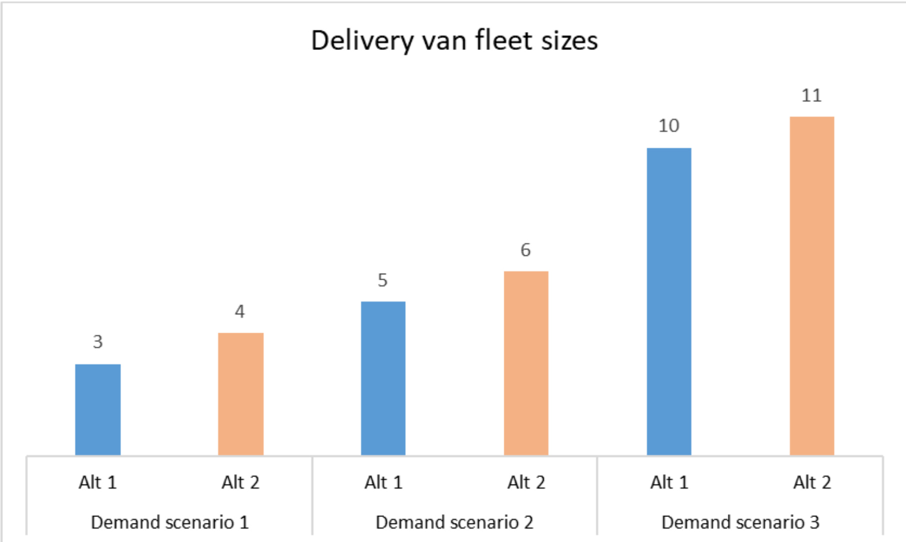


Figure 5-1: Optimal fleet sizes of delivery vans for network alt 1 and 2

Table 5-1: Solutions of CVRP models for network alt 1 and 2

Demand scenario	Alternative 1		Alternative 2	
	Fleet size (Diesel vans)	**TLC (€)**	**Fleet size** (Electric vans)	**TLC (€)**
Scenario 1 *(260 customers)*	3	451.4	4	584.3
Scenario 2 *(500 customers)*	5	740.9	6	876.4
Scenario 3*(950 customers)*	10	1457.5	11	1606.8

5.1.2 Solutions of approximated 2E-LRPs

The cost-optimal configurations of network alt 3 and 4 obtained by solving their corresponding approximate 2E-LRPs is discussed in this section. Firstly the outputs from the iterative solver algorithm and the overall solution of the approximate 2E-LRPs are presented. Next, the solutions of the subproblems integral to the approximate 2E-LRP are discussed.

5.1.2.1 Outputs of the iterative solver algorithm:

In the process of solving the approximated 2E-LRPs corresponding to network alternatives 3 and 4, the plots of minimum TLC vs. the number of clusters n_c obtained as outputs of the iterative solver algorithm is shown in Figure 5-2 and Figure 5-3. It is evident from these plots that minimum TLC value initially decreases as the value of n_c increases from its minimum (n_{min}). However, after a certain point, increasing the n_c causes a rise in the minimum TLC values. This raise in TLC indicates that decreasing the size of customer clusters beyond a certain threshold will lead to underutilization of LEFV's payload capacity, and this way, resulting in more LEFV trips and higher costs.

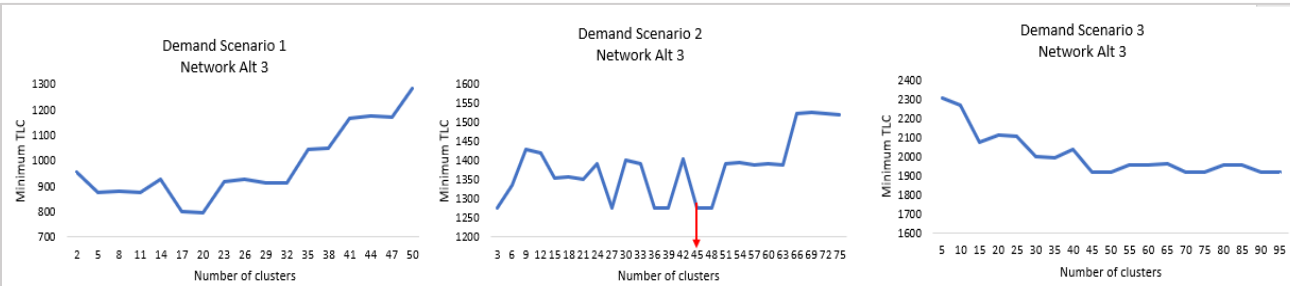


Figure 5-2:Minimum TLC vs. number of cluster plot for network alt 3

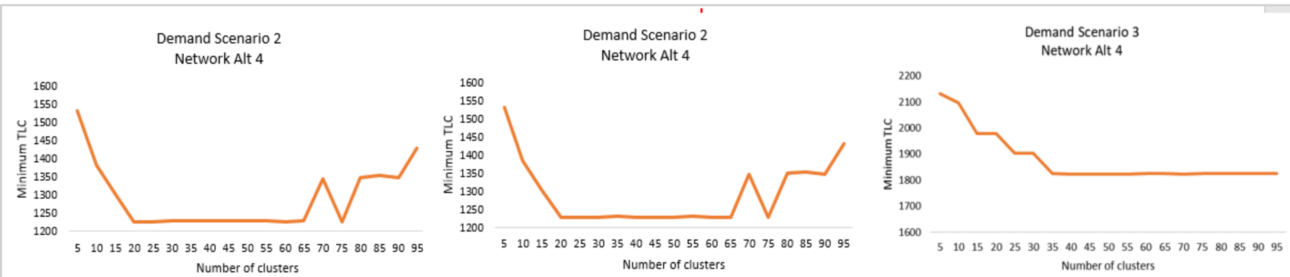


Figure 5-3:Minimum TLC vs. Number of cluster plot for network alt 4

Furthermore, there are visible peaks in the minimum TLC vs n_c plots. These peaks are likely caused by the absence of a two-way interaction between two optimization subproblems in the solver algorithm. As the algorithm directly inputs the clustering problem solution into the LFP model, variations (from the optimum) to the clustering model outputs to improve the LFP solutions are not allowed. Consequently, for a few iterations in the solver algorithm, the optimal solution obtained from the clustering algorithm is sub-optimal for the overall 2E-LRP.

Figure 5-4 shows the number of activated micro hubs and LEFV fleets size in the best cost-optimal configurations of network alternatives 3 and 4 (resulting in the lowest minimum TLC) for all three demand scenarios. It is interesting to see the difference in the number of activated micro hub locations and LEFV fleet sizes between network alt 3 and 4. For demand scenarios 2 and 3, network alt 4 utilizes either less micro hubs or smaller LEFV fleet sizes compared to that of network alt 3. This difference indicates that when the customer density is high within a LEZ, the proximity of micro hubs to customer points (locating the micro hubs inside LEZ makes) helps LEFVs to reach more customer points with fewer distances.

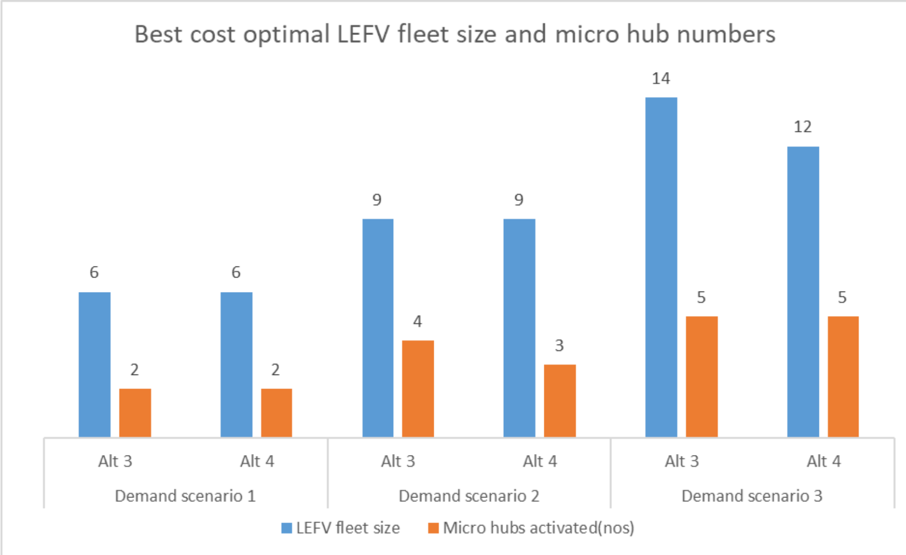


Figure 5-4:LEFV fleet size and Micro hubs activated in the cost-optimal config of network alt 3 and 4

5.1.2.2 Clustering problem solution

As discussed in Section 3.4.2.2.4, in every iteration of the approximated 2E-LRP solver algorithm, the clustering problem is first solved using a linear programming model proposed in section 3.4.2.1. During the process of solving the 2E-LRP corresponding to network alt 3 for demand scenario 2, the minimum TLC vs. plot (as shown in Figure 5-2) reveals that the best cost-optimal configuration with lowest minimum TLC is obtained in the iteration with input cluster number n_c equals to fourty-five. The clustering model outputs for this particular iteration are shown in Figure 5-5, and Figure 5-6. Figure 5-5 displays the customer points that are selected as the cluster centroids by the model. Regions with high customer density have relatively more clusters centroids compared to other regions, indicating that the model seeks to group customer points as close as possible to a cluster centroid. Furthermore, It can be observed that the chosen cluster centroids are separated from each other to the utmost level, indicating that the customers chosen as centroids are nearly in the middle of their corresponding clusters.

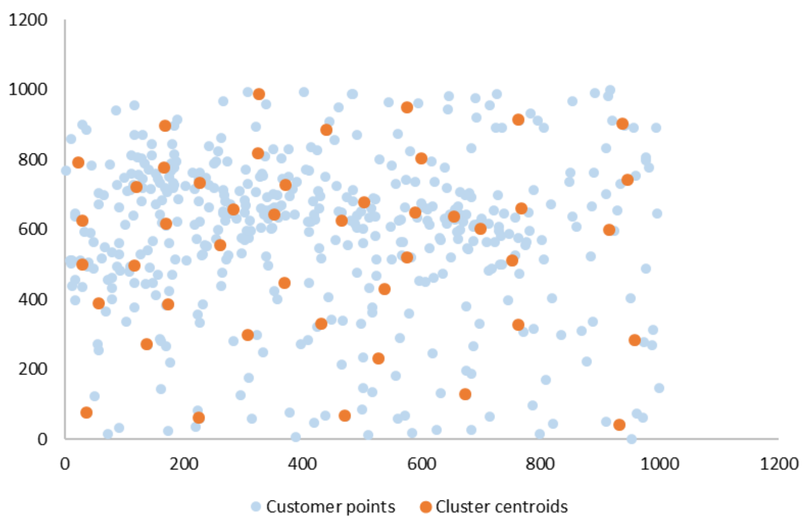


Figure 5-5:Clustering model output for network alt 3 in demand scenario 2

The frequency distribution of the number of customers in a cluster (shown in Figure 5-6) reveals that only five clusters have less than six customers, which shows that the underutilization of LEFV trips is minimal. The number of customers encompassed within each of these customer clusters is listed in appendix B. Similarly, the optimal cluster centroids for other network alternatives and demand scenarios are shown in Appendix C.

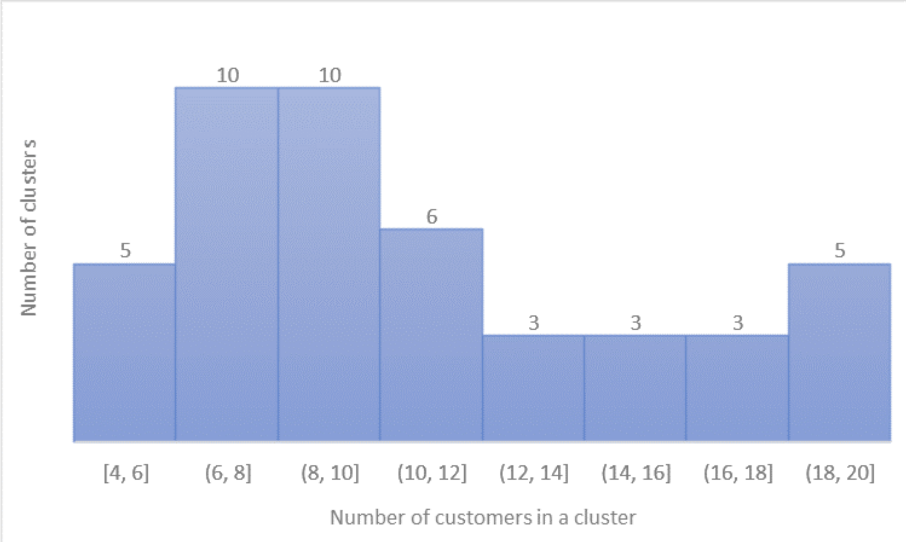


Figure 5-6: Customer distribution in clusters

5.1.2.3 Location and fleet size problem solution:

Using the solution of the clustering problem, the LFP is solved in every iteration to obtain the cost-optimal configurations of network alt 3 and 4. Similar to the previous section, the solutions of the LFP that yields the best cost-optimal configuration of network alt 3 for demand scenario 2 is discussed in this section.Figure 5-7 displays the locations of the micro hubs that are activated for operation and routes of the diesel box trucks (in the first echelon) to serve these activated micro hubs. It is important to note that the routes obtained in the first echelon from the model are likely to be much different from the real courses. The reason is that diesel box trucks are not allowed to enter the LEZ region. Nevertheless, the sequence of stops obtained from this model is still valid and can be later considered for estimating the actual routes.

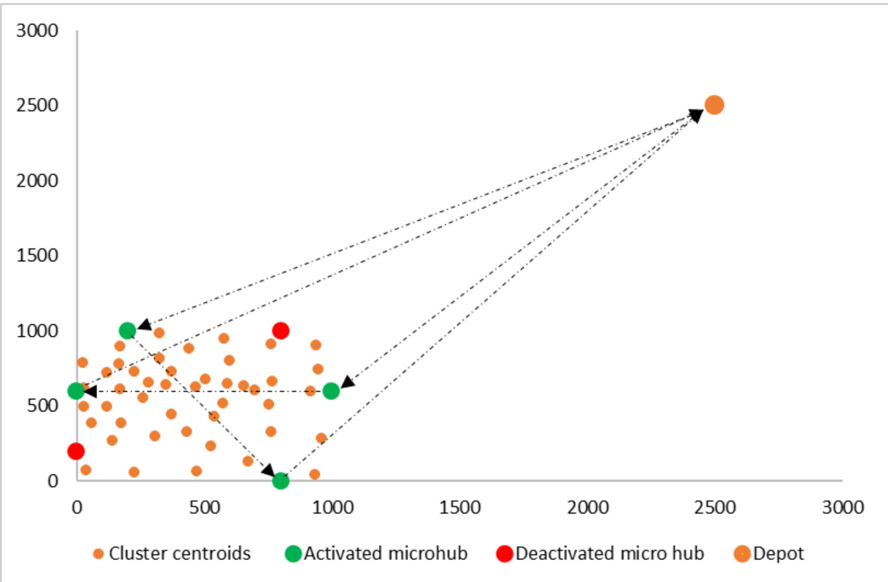


Figure 5-7:Activated micro hubs and first echelon routes in network alt 3 for demand scenario 2

Results and interpretation:

Figure 5-8 shows the allocation of the customer clusters (obtained from clustering solution) to each of these activated micro hubs in the second echelon. Finally, in Table 5-2, the LEFV fleet sizes required at each of these activated micro hubs are listed. It is observed that four micro hubs are activated by the LFP model, although three micro hubs would suffice based on their capacity. This result is likely caused due to cost trade-off between increasing LEFV fleet size to reach out to more customer points or activating another micro hub location. Furthermore, the LEFV fleet sizes and the quantities assigned to each micro hub (as shown in Table 5-2) indicate that the LEFVs are performing multiple trips from the micro hubs in a day to exploit maximally the driving ranges offered by these vehicles. The locations of the activated micro hubs for alternatives 3 and 4 in all the other demand scenarios are shown in Appendix D.

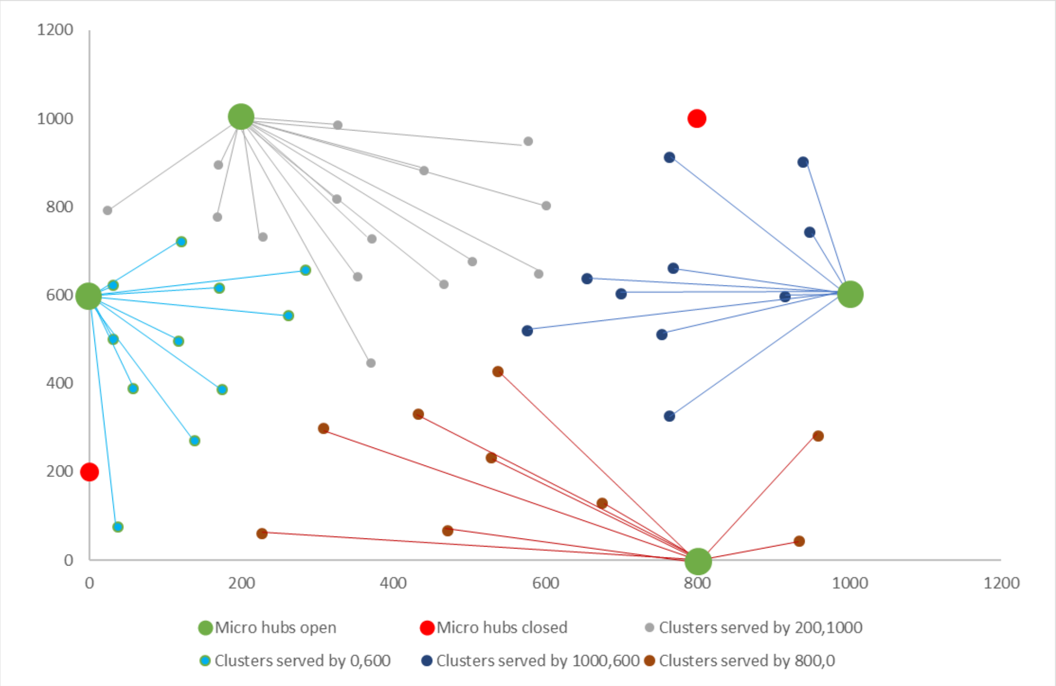


Figure 5-8:Cluster allocation to activated micro hubs in network alt 3 for demand scenario 2

Table 5-2: LRP model outputs of network alt 3 for demand scenario 2

Prospective locations of micro hubs	Activated (Yes/No)	Quantities assigned (Packages)	LEFV fleet size	Distances traveled by the LEFV
(800,1000)	No	0	0	0
(200,1000)	Yes	177	3	204.70
(0,600)	Yes	130	2	125.33
(0,200)	No	0	0	0
(1000,600)	Yes	120	2	135.36
(800,0)	Yes	73	2	139.65

5.2 VALIDATION OF THE OUTPUTS FROM THE CA METHOD

In this section, we aim to check the validity of the CA-based approach integral to the proposed approximated 2E-LRP model. The CA approach, as discussed in 3.4.2, is used to find the distance traveled by the LEFVs and the concomitant LEFV fleet sizes required at every activated micro hub. Table 5-2 shows the LEFV fleet sizes required at each activated micro hubs in the best cost-optimal configuration of network alternative 3 in demand scenario 2. As seen in the previous section, these values are obtained through CA methods. Therefore, to validate the CA approach, CVRP models (used for finding the cost-optimal configuration of network alternatives 1 and 2) can be used to find the exact routes, travel distances, and fleet sizes of LEFVs at every micro hub. For the best cost-optimal configuration of network alternative 3 for demand scenario 2, the solutions of the CVRP for activated micro hubs are shown below in Table 5-3. Comparison of the CVRP results against that of the approximated 2E-LRP model shows that both models provide with the same estimates for LEFV fleet sizes. However, the latter model estimates slightly higher values for total LEFV travel distances (average 12 km).

Table 5-3: CVRP results vs. approximated 2E-LRP results of network alt 3 for demand scenario 2

Activated micro hubs	CVRP Model outputs		Approximated 2E-LRP Model outputs		The difference in total distance traveled by LEFVs between CVRP and approximated 2E-LRP (km)
	LEFV fleet size	Total distance traveled by LEFVs (km)	LEFV fleet size	Total distance traveled by LEFVs (km)	
(200,1000)	3	191.67	3	204.7	13.03
(0,600)	2	112.54	2	125.33	12.79
(1000,600)	2	126.78	2	135.36	8.58
(800,0)	2	125.33	2	139.65	14.32
The average difference in total distance traveled by LEFV (km)					**12.18**

5.3 PERFORMANCE COMPARISON

In this section, the comparison of KPIs between network alternatives is discussed. The results are plotted across all three demand scenarios from the case study to investigate how the KPI values change with customer density. Firstly, a comparison of economic KPIs, namely *daily TLC* and *average logistics cost per unit*, is discussed, followed by the comparison of WTW emissions of vehicle fleets is performed from an environmental perspective. Later, the comparison of operational KPIs is analyzed, and a summary of results is provided.

5.3.1 Economic KPIs comparison

In Figure 5-9, the value of the *daily TLC* corresponding to the cost-optimal configurations of network alternatives are compared with each other. Additionally, the breakdown of the *daily TLC* to its fixed and variable cost components is also indicated in this figure.

Results and interpretation:

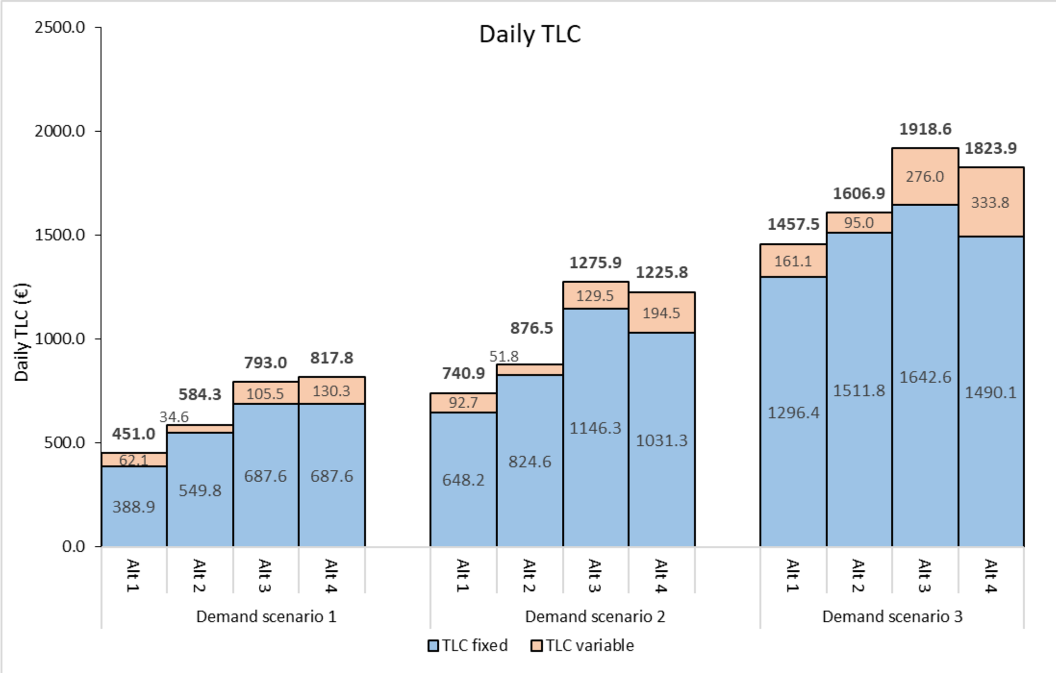


Figure 5-9:Daily TLC comparison between network alternatives

To fulfill any of the demand scenarios in the synthetic case study, *daily TLC* for network alt 1 is much lesser compared to other network alternatives, followed by network alt 2, which remains second-best across all demand scenarios. This gap indicates that network alternatives with a single echelon distribution system (network alt 1 and 2) seem to outperform the two-echelon network alternatives 3 and 4. However, Figure 5-4 shows that the average percentage increase in *daily TLC* for network alt 1 and 2 across demand scenarios is relatively higher compared to that of network alt 3 and 4. Doubling the customer density causes *daily TLC* for network alt 1 to increases on an average by 80%, whereas *daily TLCs* of network alt 3 and 4 increase by a value of 50 %. This difference implies that for a demand scenario having a customer density higher than that of considered demand scenario 3, then it is likely that the network alt 3 and 4 will potentially compete with conventional single echelon networks. Additionally, comparison of *daily TLC* values between network alt 3 and 4 shows that network alt 4 outperforms alt 3 in the other two scenarios. This result is expected as network alt 4 requires either lesser micro hubs or LEFVs compared to network alt 3 to serve demand scenarios 2 and 3 (see Section 5.1.2.3).

Table 5-4: % increase in TLC for network alternatives between demand scenarios

Last-mile delivery networks	**% increase in TLC from demand scenario 1 to 2**	**% increase in TLC from demand scenario 1 to 2**	**Average % increase in TLC**
Network Alternative 1	0.64	0.96	0.80
Network alternative 2	0.67	0.83	0.71
Network Alternative 3	0.58	0.50	0.53
Network alternative 4	0.49	0.48	0.48

Furthermore, It is interesting to see that the *average cost per unit* for network alt 3 and 4 drops significantly across the demand scenarios (refer Figure 5-10). In demand scenario 1, the *average cost per unit* for network alt 3 and 4 is much higher than that of networks 1 and 2. However, this gap almost closes in the case of demand scenario 3. Thus, the results indicate that customer density seems to have a direct effect on the economic performance of network alternatives.

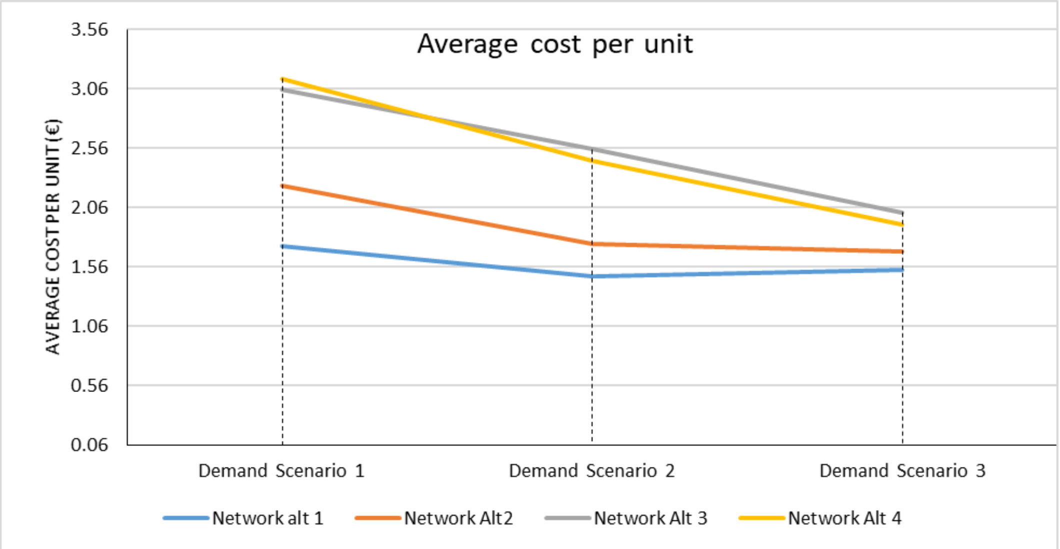


Figure 5-10:Average cost per unit vs. demand scenario for network alternatives

5.3.2 Environmental performance

Figure 5-11 compares, across all three demand scenarios, the total *WTW CO_2 emissions* from the vehicle fleets between network alternatives. Additionally, the break down of the total WTW emissions to WTT and TTW emissions are also indicated in Figure 5-11. The diesel vehicles in network alt 1 increases the level of WTW emission levels as they produce a significantly high amount of TTW emissions. In contrast, the WTW emissions from their electric counterparts in network alt 2 are much lesser as they produce zero TTW emissions. In the case of network alt 3, the TTW emissions from the box truck is a significant part of the WTW emissions, and replacing them with electric ones lowers the total WTW emissions drop as seen in the case of network alt 4. It essential to note that WTT emissions are lower when diesel vehicles are used, whereas the TTW emission level is significantly high.

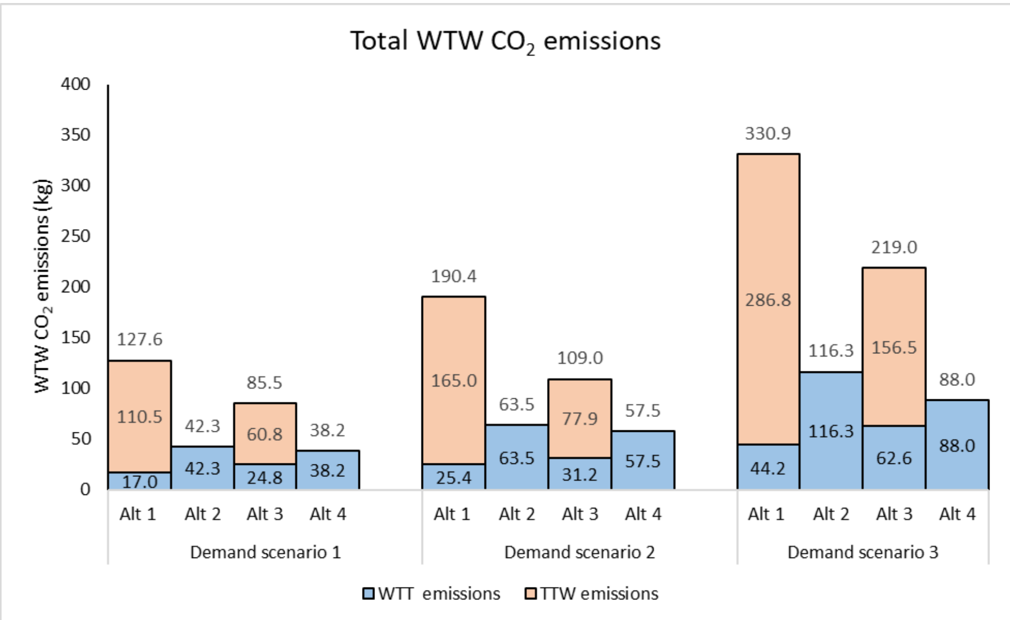


Figure 5-11:Total WTW CO2 emissions from vehicles

Results and interpretation:

Table 5-5 shows the results of the second environmental KPI- the *likelihood of adoption.* Alongside the results, The estimated minimum penalty on diesel van to shift from alternative 1 (MPDS) is shown, which is the basis of measuring the *likelihood of adoption* for network alternatives. In the case of demand scenario 1, The value of MPD for network alt 2 is always much lower than the penalty that the municipality is planning to issue for LEZ entry (95€.). Consequently, the likelihood of adopting network alt 2 is HIGH in all demand scenarios. In contrast, the likelihood of adoption for network alt 3 and 4 to serve demand scenarios 1 and 2 is LOW, because their corresponding MPD is higher than 95€. On the other hand, in the case of demand scenario 3, the *likelihood of adoption* for network alt 3 and 4 changes to HIGH. Thus, LSP in question can choose to shift from the existing network to either of these alternatives when customer density is high.

Table 5-5:Likelihood of adoption for network alternatives

Demand scenarios	*MPDS* for network alt 2 ***(likelihood of adoption)***	*MPDS* for network alt 3 ***(likelihood of adoption)***	*MPDS* for network alt 4 ***(likelihood of adoption)***
Demand scenario 1	44 € (**HIGH**)	122 € (**LOW**)	113 € (**LOW**)
Demand scenario 2	27 € (**HIGH**)	106 € (**LOW**)	96 € (**LOW**)
Demand scenario 3	14 € (**HIGH**)	46 € (**HIGH**)	36 € (**HIGH**)

5.3.3 Operational performance

As discussed in the section, the operational performance of network alternatives is compared based on the two KPIs, *total operation times*, and *average service time per customer.* Figure 5-12 compares the *total operation times* for all four network alternatives, along with break down to traveling time and handling time. It is evident that in all three demand scenarios, network alt 1 takes the lowest time to finish its operations. The handling time of network alt 2 remains the same as network alt 1, but the larger fleet sizes in the former cause a corresponding increase in the travel times. Even though LEFV is significantly fast on urban roads(refer Section 4.5), the additional time required for box truck fleets to unload at the micro hubs increases the *total operation time*. However, it is interesting to see that the vehicle travel time in alternative 4 is lesser compared to network alt 3 when serving demand scenario 3. The reason for this could be the proximity of micro hubs to customer points and the smaller LEFV fleet sizes (see Section 5.1.2.3).

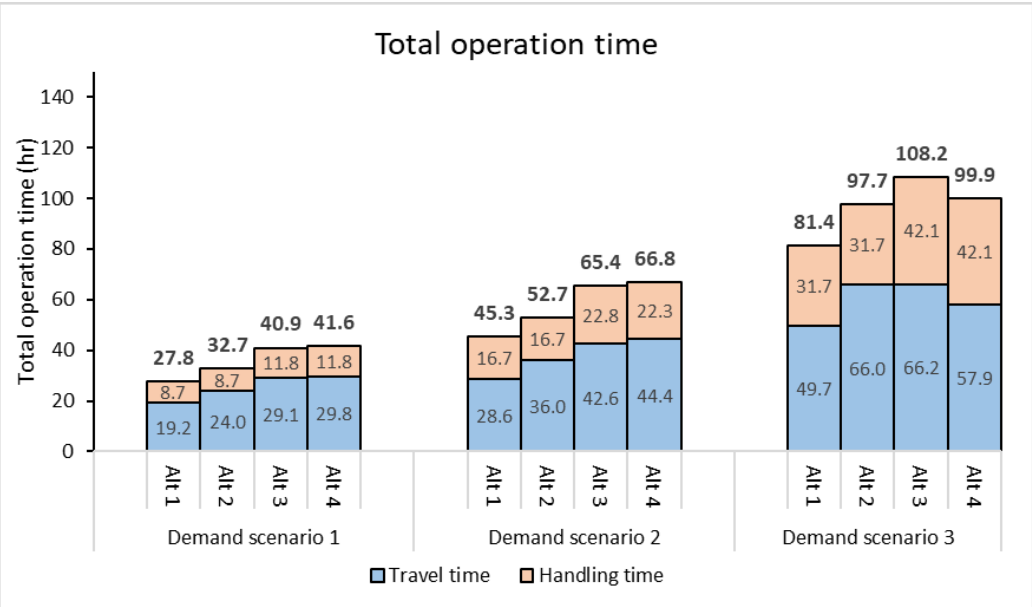


Figure 5-12:Total operation time for network alternatives

In Figure 5-13, the *average service time per customer* for network alternatives is plotted across the demand scenarios. Network alternatives 3 and 4 requires, on average, more time to serve a customer compared to network alternatives 1 and 2. However, this gap closes across demand scenarios. As the customer density increases across the demand scenarios, the rate at which this KPI drops is higher for alternatives 3 and 4 compared to alternatives 1 and 2. Notably, the drop is significant for network alternative 4 compared to 3. In demand scenario 2, average service time per parcel is slightly lesser for network alt 3 compared to alt 4. However, for demand scenario 4, network alternative 4 costs considerably less than network alt 3.

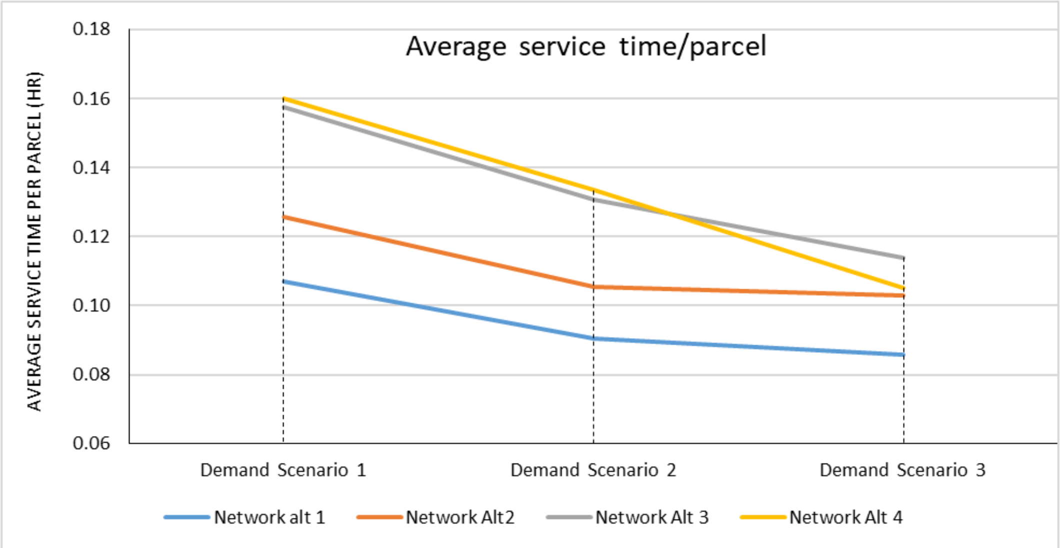


Figure 5-13:Average service time per customer for all network alternatives

5.3.4 Summary of performance comparison

The comparison of economic KPIs shows that the rate at which *daily TLC* of network alternatives 3 and 4 increases with LEZ's customer density is lower compared to that of network alternatives 1 and 2. Consequently, the *average cost per unit* also drops significantly for network alternatives 3 and 4 compared to network alternatives 1 and 2 as customer density increases. Both these results indicate that that conventional single echelon network alternatives cost compared to urban transshipment network hubs when customer density within LEZ is low. On the contrary, when the customer density is high, the urban transshipment networks can cost the same or lesser compared with conventional networks. The results of operational KPI performance comparison are similar to the results of economic KPIs. Network alternatives 3 and 4 require high service times compared to network alternatives 1 and 2 when customer densities within LEZ are low. However, average service time per customer drops significantly for network alternatives 3 and 4 as customer density increases. Therefore the results of the average cost per unit and average service time per customer show that network alternatives with micro hubs and LEFV leverage economies of scale better compared to conventional single echelon network alternatives. Additionally, it is observed that network alternative 4 performs better, both economically and operationally, compared to network alternative 3 provided the customer densities are high.

The analysis of environmental KPIs showed that the network performed very low as they employ high polluting diesel vans. On the other hand, network alternatives 2 and 4 produced the lowest amount of WTW emissions. Notably, network alternative 4 performed the best among all four network alternatives, indicating that urban transshipment networks can result in lesser emissions than a single echelon network. The analysis of the likelihood of adoption suggests that the possibility of LSP to change from existing network alternatives 3 and 4 is low when customer density in LEZ is low, implying that network alternative 2 is likely to be adapted.

Results and interpretation:

Nevertheless, taking account of the results of previous KPIs, network alternatives 3 and 4 may be chosen over network alt 2 to serve a LEZ with high customer density. The reason is that network alternatives 3 and 4 can leverage economies of scale better and perform either equally well from an environmental perspective.

6 DISCUSSION, CONCLUSIONS, AND LIMITATIONS

In this chapter, the discussion and conclusion for the research are provided. Subsequently, limitations of the present research and opportunities for future research are explained.

6.1 DISCUSSION

This section firstly discusses the adopted methodology with a focus on the approach, models, and assumptions that are made. Later, the case study results are discussed.

6.1.1 Methodology

This research proposes a DST for LSPs to strategically evaluate the performance of urban transshipment networks with LEFVs for providing last-mile delivery service within a LEZ. The DST is proposed mainly due to two reasons. Firstly, ex-ante performance evaluation of new logistics networks is crucial as their adoption in real-life involves a significant commitment of LSP's resources over an extended period. Second, executing the process before any form of application (trials /pilots) is complex as the data required for performance measurement is not readily available to conduct analysis. In the latter context, network optimizations models are integrated into the proposed DST to derive the data required for measuring the performance of a network.

Similarly, Amodeo et al. (2015) argue that network optimization models help in simulating the resulting distribution activity because it is logical for an LSP to adopt a cost-optimal network configuration. The network optimization models, used in the proposed DST, determines the network configurations that result in minimum TLCs. The proposed DST measures the performance of logistics networks based on their minimum TLC configurations. This assumption is in line with Rybakov (2017), where the author argues for designing a logistics network such that the TLC is optimized, rather than separate optimized logistics cost elements.

Four different network alternatives are evaluated within the DST, whose structures are assumed to be generalized. Two network alternatives are based on single echelon distribution systems and homogeneous vehicle fleets. Whereas, the other two are urban transshipment network with micro hubs and homogeneous LEFV fleets. The LSP in question is assumed to be currently employing a network alternative with a single echelon distribution system with diesel vehicles for their last-mile delivery services. However, Janjevic et al. (2013) show that LSPs usually arrange their networks in several creative ways such as multi-echelon systems, urban consolidation centers, and mixed vehicle fleets. Additionally, a scenarios-based framework is adopted in the proposed DST to analyze multiple what-if situations.

A set of two optimization models is used for determining cost-optimal network configurations of network alternatives. Standard CVRP models are used for single echelon network alternatives, while a new optimization model based on CA methods is proposed for urban transshipment type networks. The proposed model comprises of two interconnected sub-models, clustering problem and location and fleet size problem model. Solving the proposed model involves solving the two sub-models such that the output of the clustering model is input for location and fleet size problem. An iterative algorithm is developed to solve these two sub-models for a hierarchy of clusters for finding the best cost-optimal network configuration. The proposed model is offered as a substitute for the existing models as they combine two NP-hard problems and hard to apply in real-life contexts (Prodhon & Prins, 2014). Although the new model does not result in the precise data, it still provides a close approximate to the global optimum. The clustering-based model developed in this research is similar to the tour scheduling model recently developed by Chiara et al. (2020). This model firstly divides the given customer distribution into a hierarchy of disjoint clusters and then determines the fleet size of cargo bikes or delivery vans to serve these clusters using a CVRP. Furthermore, similar to the proposed DST, this tour scheduling model was an integral part of a meta-framework that was operationalized by demand and operational scenarios. These operational scenarios are similar to the network alternatives used in this research. Finally, the performance of each network's performance is measured using the predefined KPIs, which demonstrate how a network alternative meets the goals of organizations involved in fast-moving consumer goods sectors. (Paddeu, D. 2016).

The application of the DST on the synthetic case study has demonstrated the capability of this model to assist LSPs in evaluating the performance of the urban transshipment network. The proposed model can simulate closely the network configuration, which will be adopted by an LSP and to derive the quantitively the data adequate for its strategic performance evaluation. The model also is capable of solving large realistic problems with above 900 customer points without the need for sophisticated solving approaches.

6.1.2 Results:

It is essential to bear in mind that the case study results shown in the previous chapter do not represent the actual performances of the network alternatives. However, it shows how urban transshipment networks with electric vehicles compete against conventional single echelon networks in last-mile distribution.

Form an economic standpoint, the performance comparison results show that network alt 1 with a single echelon distribution network and diesel delivery vans outperforms all other network alternatives in all three demand scenarios considered in the case study. Followed by network alt 1, network alt 2 with battery-electric vans and a single echelon distribution system, is visibly the next best economic option. On the other hand, two-echelon based urban transshipment networks with LEFVs are unable to compete, economically, with single echelon network alternatives for all demand scenario considered in the case study. Nevertheless, as customer density nearly doubles within the demand scenarios, the average cost per parcel for urban transshipment network alternatives drops significantly. Therefore, indicating that urban transshipment network with electric vehicles could outperform or match single echelon networks in case of the customer density within the LEZ is very high.

The result, thus obtained, is in line with the study by Ballare & Lin, (2020), where the results showed that the performance of a crowd shipping powered micro hub network significantly increased with an increase in customer density. Similar to economic performance, the operational performance of urban transshipment networks with LEFV improved as customer density increased. The average delivery time per parcel of an urban transshipment network converges to that of a conventional network when customer density grows. The results of both economic and operational KPIs indicate that the urban transshipment network with LEFVs allows LSP to leverage economies of scale more efficiently than single echelon network alternatives.

From an environmental perspective, the conventional network alternative results in the highest WTW emissions level as the fleet of diesel vehicles produce significantly high levels of TTW emissions. Compared to this alternative, the remaining three alternatives cause much lesser WTW emissions. More importantly, these TTW emissions negatively affect air quality in urban spaces but, TTW emissions from electric vehicles result in emissions far away from the city (close to the production). In this way, electric vehicles help to reduce the externalities of last-mile transport in urban areas. Notably, urban transshipment network with electric vehicles adopted at both echelons shows the highest potential in meeting with such urban transport sustainable goals. However, considering that LSP is more inclined towards their financial goals, the likelihood of LSPs to adopt an urban transshipment network from a conventional network for serving a LEZ with low customer density is faint. The reason is that excess costs required to incorporate these new networks are more than the costs incurred in the form of penalties on diesel vehicle entry into LEZ. The LSP is likely to substitute the diesel vans with electric vans for such instances. On the contrary, the results show that the LEZ entry penalty encourages the adoption of the urban transshipment network if the density of customer points in LEZ is high. The results obtained are in line with the insights from expert interviews by Dablanc & Montenon (2015), which showed that the introduction of legal restrictions such as LEZ compels large LSPs to incorporate electric vehicles and private hub networks.

Finally, the results highlighted the importance of locating the micro hubs close to the point of reception. By doing so, it was evident that urban transshipment networks perform better, economically, operationally, and environmentally. Similarly, Muñuzuri et al. (2012) highlighted the importance of centrally located micro hubs. All of this indicates that when considering an option to shift to an urban transshipment network, LSPs will consider locating the micro hubs inside the LEZ even though it is required to use heavy electric freight vehicles in the first echelon**.**

6.2 Conclusion

Although several different factors influence the performance of a logistics network, this research has used operations research techniques to virtually evaluate new transshipment based networks for the last mile. In this section, we answer the sub-questions, followed by the final question.

> ***RQ1**: What are the main criteria to evaluate the performance of the urban transshipment network from the perspective of a private logistics firm?*

Commonly, LSPs are private-owned companies seek to increase their profits, ensure customer satisfaction, and meeting with all the legal regulations. However, over recent years, the increased awareness about negative externalities and pressure form national organizations has forced LSP to establish sustainability goals. Therefore, accounting for all these goals, the present research has adopted KPIs from an economic, operational, and environmental perspective. Economic KPIs include total logistics cost, the average cost per unit, whereas operational KPI involves total operating times, and average service time per customer. Environmental KPIs involves the WTW CO_2 emissions from vehicle fleets and the likelihood to shift from conventional high polluting networks to less polluting network alternatives.

> ***RQ2**: What is the data or information required to evaluate the performance of this network?*

Two different data sets are required to evaluate the performance of urban transshipment networks. The first set of data includes all the exogenous information inputted into the DST, which includes the prices, specifications of vehicle fleets, and micro hubs used in network alternatives. Furthermore, the WTT and TTW CO_2 emissions and average handling times per vehicle mode are also inputted exogenously to the DST. The exogenous data set can be accumulated through market research, previous studies or pilots, or from a consultancy company that has worked on similar projects (as in the case of this research). The second set of data must be obtained endogenously, which includes the cost-optimal network configurations and the distances traveled by the vehicle fleets. The cost-optimal configuration provides with size, locations, and the number of micro hubs and vehicles in the urban transshipment network.

> ***RQ3**: What is the baseline for the performance evaluation of the urban transshipment network?*

In this research, a performance comparison between the urban transshipment network and other plausible network substitutes is drawn in parallel. The other networks used for comparison include single echelon distribution networks with diesel or electric vehicles, for which the set of data is accumulated or obtained similar to that of an urban transshipment network. The performance of these networks acts as the baseline for evaluating the performance of urban transshipment networks.

***RQ4*: What model can be used to get the data required for performance assessment?**

A set of two different optimization models is employed to obtain the minimum TLC configuration and distances traveled by vehicle fleets of network alternatives. CVRP model is used in the case of single echelon networks, while a new CA-based optimization model is employed for urban transshipment networks. The proposed CA-based model constitutes two distinct, but interconnected sub-models called the clustering model and location routing model. The clustering model firstly determines the disjoint customer clusters and then approximates the distance traveled by vehicles within these clusters. Next, using the outputs of clustering models as inputs, the Location fleet size problem determines the minimum TLC configuration of the network.

Main RQ*: How to evaluate the performance of urban transshipment network with electric vehicles in low emission zone?*

This research proposes an optimization model-driven decision support tool to assist logistics service providers in evaluating the performance of urban transshipment networks with electric vehicles for their last-mile deliveries within a LEZ. The proposed tool can virtually replicate the configuration of the network that would be employed and the corresponding data about distribution activities. The tool has proved its capability to obtain reliable data that is required by LSP to check the effectiveness of urban transshipment networks towards achieving organizational goals.

6.3 LIMITATIONS AND FUTURE WORK:

Although last-mile delivery networks are the final phase of distribution of the supply chain involving the LSP and the customer, there are still several aspects that could be accounted to reproduce their distribution activities in reality. Incorporating all these aspects may not only complicate the process of developing the model but also impede understanding of the model for the logistics practitioners. Thus, the primary challenge of this research was to use analytical approximation methods to aggregate operational details such that strategic information could be derived easily. Therefore, allowing LSPs to test multiple input values without much complexity. However, opportunities to improve the proposed model and extending the DST are identified for future work.

- **Improvements to the iterative solution algorithm**: As explained in Section 5.1.2.1, the solver algorithm proposed for solving the approximate 2E-LRP model was missing a dynamic improvement link between the clustering model and the LRP. This missing link caused the peaks in minimum TLC vs. the number of clusters n_c plots. Therefore, the development of a new heuristic solution procedure integrated with this improvement link can result in a solution closer to the optimum global point.

- **Sophisticated approximation and optimization models**: Extension to the CA model by Figliozzi (2008) was developed by Winkenbach et al. (2016), called as augmented routing cost estimation formula .This approximation formula accounts for different vehicle capacities, service times, and combined pickup and delivery routes. Thus, integrating this approximation method could estimate, precisely, the distances traveled by the LEFVs in last-mile delivery services. Furthermore, the integer linear LRP model can be extended to allow multiple product flow; heterogenous vehicles fleet both at the depot as well at micro hubs, customer delivery routes starting from micro hubs as well as the depot.

- **Creative network alternatives**: In the present research, only a single echelon or two-echelon distribution networks are considered. However, as turnover is a critical factor for economic performance of such networks, a third echelon can be added to the last-mile delivery network to bundle the deliveries together in an urban consolidation center. Evaluating the performance of such innovative schemes would require extending the approximated 2E-LRP model to cope with multiple echelons.

- **Extending the use of decision support framework**: Although the proposed DST is intended to assist private logistics firms, the DST can also be applied by public authorities to evaluate the impact of their LEZ polices on LSPs engaged in last-mile delivery services. The LEZ area and entry penalties can be varied across demand scenarios to predict the resulting network adaptations by a typical LSP. Furthermore, The DST can be integrated into an agent-based simulation to check how LSPs having different customer densities will change their operations if LEZ is introduced into their service regions.

REFERENCES

Abdallah, H. (2004). Guidelines for Assessing Costs in a Logistics System - An Example of Transport Cost Analysis. *Arlington, Va.: John Snow, Inc./DELIVER, for the US Agency for International Development*, 37.

Amodeo, L., Lamari, D., Musolino, G., Placido, V., Polimeni, A., Praticò, M., & Vitetta, A. (2015). An ex-ante evaluation of last-mile freight distribution services for city logistics. In *Urban Transport XXI* (Vol. 1, pp. 291–302). WIT Press. https://doi.org/10.2495/ut150231

Ansari, S., Başdere, M., Li, X., Ouyang, Y., & Smilowitz, K. (2018, January 1). Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. *Transportation Research Part B: Methodological*. Elsevier Ltd. https://doi.org/10.1016/j.trb.2017.09.019

Aykin, T. (1995). The hub location and routing problem. *European Journal of Operational Research*, *83*(1), 200–219. https://doi.org/10.1016/0377-2217(93)E0173-U

Baldacci, R., Hadjiconstantinou, E., & Mingozzi, A. (2004). An exact algorithm for the capacitated vehicle routing problem based on a two-commodity network flow formulation. *Operations Research*, *52*(5), 723–738. https://doi.org/10.1287/opre.1040.0111

Ballare, S., & Lin, J. (2020). Investigating the use of microhubs and crowdshipping for last mile delivery. In *Transportation Research Procedia* (Vol. 46, pp. 277–284). Elsevier B.V. https://doi.org/10.1016/j.trpro.2020.03.191

Balm, S., Moolenburgh, E., Anand, N., & Ploos van Amstel, W. (2018). The Potential of Light Electric Vehicles for Specific Freight Flows: Insights from the Netherlands. In *City Logistics 2* (pp. 241–260). https://doi.org/10.1002/9781119425526.ch15

Beardwood, J., Halton, J. H., & Hammersley, J. M. (1959). The shortest path through many points. *Mathematical Proceedings of the Cambridge Philosophical Society*, *55*(4), 299–327. https://doi.org/10.1017/S0305004100034095

BEIS. (2019). Greenhouse gas reporting: conversion factors 2019 - GOV.UK. Retrieved June 27, 2020, from https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2019

Boccia, M., Crainic, T. G., Sforza, A., & Sterle, C. (2010). A metaheuristic for a two echelon location-routing problem. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 6049 LNCS, pp. 288–301). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-13193-6_25

Buldeo Rai, H., Verlinde, S., & Macharis, C. (2019). The “next day, free delivery” myth unravelled: Possibilities for sustainable last mile transport in an omnichannel environment. *International Journal of Retail and Distribution Management*, *47*(1), 39–54. https://doi.org/10.1108/IJRDM-06-2018-0104

Chiara, G. D., Alho, A. R., Cheng, C., Ben-Akiva, M., & Cheah, L. (2020). Exploring Benefits of Cargo-Cycles versus Trucks for Urban Parcel Delivery under Different Demand Scenarios. *Transportation Research Record: Journal of the Transportation Research Board*, 036119812091716. https://doi.org/10.1177/0361198120917162

Clarke, S., & Leonardi, J. (n.d.). *Consolidating deliveries of retail and non-retail clients into single electric van deliveries*. Retrieved from www.london.gov.uk

Cleophas, C., & Ehmke, J. F. (2014). When are deliveries profitable. *Business and Information Systems Engineering*, *6*(3), 153–163. https://doi.org/10.1007/s12599-014-0321-9

Contardo, C., Cordeau, J. F., & Gendron, B. (2013). A computational comparison of flow formulations for the capacitated location-routing problem. *Discrete Optimization*, *10*(4), 263–295. https://doi.org/10.1016/j.disopt.2013.07.005

Contardo, C., Hemmelmayr, V., & Crainic, T. G. (2012). Lower and upper bounds for the two-echelon capacitated location-routing problem. *Computers and Operations Research*, *39*(12), 3185–3199. https://doi.org/10.1016/j.cor.2012.04.003

Crainic, T.G., Sforza, A., & Sterle, C. (2011). Location-Routing Models for Two-Echelon Freight Distribution System Design Location-Routing Models for Two-Echelon Freight. *CIRRELT Working Paper*, 28. Retrieved from www.cirrelt.ca

Crainic, Teodor Gabriel, 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

Crainic, Teodor Gabriel, Sforza, A., & Sterle, C. (2011). *Location-Routing Models for Two-Echelon Freight Distribution System Design Bureaux de Montréal : Bureaux de Québec*. Retrieved from www.cirrelt.ca

Cuda, R., Guastaroba, G., & Speranza, M. G. (2015a). A survey on two-echelon routing problems. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2014.06.008

Cuda, R., Guastaroba, G., & Speranza, M. G. (2015b). A survey on two-echelon routing problems. *Computers and Operations Research*, *55*, 185–199. https://doi.org/10.1016/j.cor.2014.06.008

Dablanc, L., & Montenon, A. (2015a). Impacts of environmental access restrictions on freight delivery activities example of low emissions zones in Europe. *Transportation Research Record*, *2478*, 12–18. https://doi.org/10.3141/2478-02

Dablanc, L., & Montenon, A. (2015b). Impacts of environmental access restrictions on freight delivery activities example of low emissions zones in Europe. *Transportation Research Record*, *2478*, 12–18. https://doi.org/10.3141/2478-02

Davis, B. A., & Figliozzi, M. A. (2013). A methodology to evaluate the competitiveness of electric delivery trucks. *Transportation Research Part E: Logistics and Transportation Review*, *49*(1), 8–23. https://doi.org/10.1016/j.tre.2012.07.003

Drexl, M., & Schneider, M. (2015, March 1). A survey of variants and extensions of the location-routing problem. *European Journal of Operational Research*. Elsevier. https://doi.org/10.1016/j.ejor.2014.08.030

Duarte, G., Rolim, C., & Baptista, P. (2016). How battery electric vehicles can contribute to sustainable urban logistics: A real-world application in Lisbon, Portugal. *Sustainable Energy Technologies and Assessments*, *15*, 71–78. https://doi.org/10.1016/j.seta.2016.03.006

European Association for Battery Electric Vehicles. (2009). Energy consumption , CO2 emissions and other considerations related to Battery Electric Vehicles. *Energy*, (April 2009), 1–21.

Figliozzi, M. A. (2008). Planning approximations to the average length of vehicle routing problems with varying customer demands and routing constraints. *Transportation Research Record*, *2089*(2089), 1–8. https://doi.org/10.3141/2089-01

Frota Neto, J. Q., Bloemhof-Ruwaard, J. M., van Nunen, J. A. E. E., & van Heck, E. (2008). Designing and evaluating sustainable logistics networks. *International Journal of Production Economics*, *111*(2), 195–208. https://doi.org/10.1016/j.ijpe.2006.10.014

Gao, S., Wang, Y., Cheng, J., Inazumi, Y., & Tang, Z. (2016). Ant colony optimization with clustering for solving the dynamic location routing problem. *Applied Mathematics and Computation*, *285*, 149–173.

https://doi.org/10.1016/j.amc.2016.03.035

Gruber, J., & Narayanan, S. (2019). Travel Time Differences between Cargo Cycles and Cars in Commercial Transport Operations. *Transportation Research Record*. https://doi.org/10.1177/0361198119843088

Guerrero, J. C., & Díaz-Ramírez, J. (2017). A review on transportation last-mile network design and urban freight vehicles. In *Proceedings of the International Conference on Industrial Engineering and Operations Management* (Vol. 2017, pp. 533–552).

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. In *International Journal of Production Economics* (Vol. 87, pp. 333–347). Elsevier. https://doi.org/10.1016/j.ijpe.2003.08.003

Hogt, R., Balm, S., & Warmerdam, J. (n.d.). *Designing Light Electric Vehicles for urban freight transport*.

Huang, Y. K., Feng, C. M., & Wu, P. J. (2009). A structural equation model of management strategies and firm performance: A case study of logistics service quality on home delivery. *International Journal of Electronic Customer Relationship Management*, *3*(3), 281–300. https://doi.org/10.1504/IJECRM.2009.027954

Huber, S., Klauenberg, J., & Thaller, C. (2015). Consideration of transport logistics hubs in freight transport demand models. *European Transport Research Review*, *7*(4), 1–14. https://doi.org/10.1007/s12544-015-0181-5

Janjevic, M., Kaminsky, P., & Ballé Ndiaye, A. (2013). Downscaling the consolidation of goods – state of the art and transferability of micro-consolidation initiatives.

Lebeau, P., Macharis, C., & Van Mierlo, J. (2013). How to Improve the Total Cost of Ownership of Electric Vehicles: An Analysis of the Light Commercial Vehicle Segment. *World Electric Vehicle Journal*, *10*(4), 90. https://doi.org/10.3390/wevj10040090

Lebeau, P., Macharis, C., Van Mierlo, J., & Lebeau, K. (2015). Electrifying light commercial vehicles for city logistics? A total cost of ownership analysis. *European Journal of Transport and Infrastructure Research*, *15*(4), 551–569. https://doi.org/10.18757/ejtir.2015.15.4.3097

Lee, J., Kim, C., & Wiginton, L. (2019). *Delivering Last-Mile Solutions: A feasibility analysis of microhubs and cyclelogistics in the GTHA*. Retrieved from https://www.pembina.org/reports/delivering-last-mile-solutions-june-2019.pdf

Lenz, B., & Riehle, E. (2013). Bikes for urban freight? *Transportation Research Record*, *2379*(2379), 39–45. https://doi.org/10.3141/2379-05

Leonardi, J., Browne, M., & Allen, J. (2012). Before-After Assessment of a Logistics Trial with Clean Urban Freight Vehicles: A Case Study in London. *Procedia - Social and Behavioral Sciences*, *39*, 146–157. https://doi.org/10.1016/j.sbspro.2012.03.097

Leonardi, J., Dabalanc, L., Van Egmond, P., & Guerlain, C. (2015). Feasibility Study of a Network of Consolidation Centres in Luxembourg.

LocalSolver: CVRP. Retrieved June 24, 2020, from https://www.localsolver.com/benchmarkcvrp.html

Melo, S., & Baptista, P. (2017). Evaluating the impacts of using cargo cycles on urban logistics: integrating traffic, environmental and operational boundaries. *European Transport Research Review*, *9*(2), 30. https://doi.org/10.1007/s12544-017-0246-8

Merchan, D., Blanco, E. E., & Winkenbach, M. (2016). Transshipment networks for last-mile delivery in congested urban areas. In *ILS 2016 - 6th International Conference on Information Systems, Logistics and Supply Chain*.

Muñuzuri, J., Cortés, P., Grosso, R., & Guadix, J. (2012). Selecting the location of minihubs for freight delivery in congested downtown areas. *Journal of Computational Science*, *3*(4), 228–237. https://doi.org/10.1016/j.jocs.2011.12.002

Nagy, G., & Salhi, S. (2006). Location-routing: Issues, models and methods. *European Journal of Operational Research*, *177*(2), 649–672. https://doi.org/10.1016/j.ejor.2006.04.004

Oliveira, C., Albergaria De Mello Bandeira, R., Vasconcelos Goes, G., Schmitz Gonçalves, D., & D'Agosto, M. (2017). Sustainable Vehicles-Based Alternatives in Last Mile Distribution of Urban Freight Transport: A Systematic Literature Review. *Sustainability*, *9*(8), 1324. https://doi.org/10.3390/su9081324

Olsson, J., Hellström, D., & Pålsson, H. (2019). Framework of last mile logistics research: A systematic review of the literature. *Sustainability (Switzerland)*, *11*(24), 1–25. https://doi.org/10.3390/su11247131

Ploos Van Amstel, W., Balm, S., Warmerdam, J., Boerema, M., Altenburg, M., Rieck, F., & Peters, T. (2018). *Urban Technology Research Programme Lefv-Logic: Research on Light Electric Freight Vehicles*.

Prodhon, C., & Prins, C. (2014, October 1). A survey of recent research on location-routing problems. *European Journal of Operational Research*. Elsevier. https://doi.org/10.1016/j.ejor.2014.01.005

Quak, H., Nesterova, N., & Van Rooijen, T. (2016). Possibilities and Barriers for Using Electric-powered Vehicles in City Logistics Practice. In *Transportation Research Procedia*. https://doi.org/10.1016/j.trpro.2016.02.055

Rybakov, D. S. (2017). Total cost optimisation model for logistics systems of trading companies. *International Journal of Logistics Systems and Management*, *27*(3), 318. https://doi.org/10.1504/ijlsm.2017.084469

Seebauer, S., Kulmer, V., Bruckner, M., & Winkler, E. (2016). Carbon emissions of retail channels: the limits of available policy instruments to achieve absolute reductions. *Journal of Cleaner Production*, *132*, 192–203. https://doi.org/10.1016/j.jclepro.2015.02.028

Simoni, M. D., Bujanovic, P., Boyles, S. D., & Kutanoglu, E. (2018). Urban consolidation solutions for parcel delivery considering location, fleet and route choice. *Case Studies on Transport Policy*, *6*(1), 112–124. https://doi.org/10.1016/j.cstp.2017.11.002

Škrinjar, J. P., Rogić, K., & Stanković, R. (2012). Location of urban logistic terminals as hub location problem. *Promet - Traffic - Traffico*, *24*(5), 433–440. https://doi.org/10.7307/ptt.v24i5.1179

Soares, C. D. (2012). Annex 5 : Subsidy level indicators for the case studies, 1–26. Retrieved from http://ec.europa.eu/energy/publications/statistics/doc/2009_energy_transport_figures.pdf

Taefi, T. T., Kreutzfeldt, J., Held, T., & Fink, A. (2015). Strategies to increase the profitability of electric vehicles in urban freight transport. *Green Energy and Technology*, *203*, 367–388. https://doi.org/10.1007/978-3-319-13194-8_20

Tragantalerngsak, S., Holt, J., & Rönnqvist, M. (2000). Exact method for the two-echelon, single-source, capacitated facility location problem. *European Journal of Operational Research*, *123*(3), 473–489. https://doi.org/10.1016/S0377-2217(99)00105-8

Uchoa, E., Pecin, D., Pessoa, A., Poggi, M., Vidal, T., & Subramanian, A. (2017). New benchmark instances for the Capacitated Vehicle Routing Problem. *European Journal of Operational Research*, *257*(3), 845–858. https://doi.org/10.1016/j.ejor.2016.08.012

Van Duin, J. H. R., Tavasszy, L. A., & Quak, H. J. (2013). Towards E(lectric)-urban freight: First promising steps in the electric vehicle revolution. *European Transport - Trasporti Europei*, (54).

Van Loon, P., Deketele, L., Dewaele, J., McKinnon, A., & Rutherford, C. (2015). A comparative analysis of carbon emissions from online retailing of fast moving consumer goods. In *Journal of Cleaner Production*

(Vol. 106, pp. 478–486). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2014.06.060

Wang, M., Thoben, K.-D., Bernardo, M., & Daudi, M. (2018). Diversity in Employment of Electric Commercial Vehicles in Urban Freight Transport: A Literature Review. *Logistics Research*, *11*(1), 1–21. https://doi.org/10.23773/2018_10

Winkenbach, M., Kleindorfer, P. R., & Spinler, S. (2016). Enabling urban logistics services at la poste through multi-echelon location-routing. *Transportation Science*, *50*(2), 520–540. https://doi.org/10.1287/trsc.2015.0624

APPENDIX

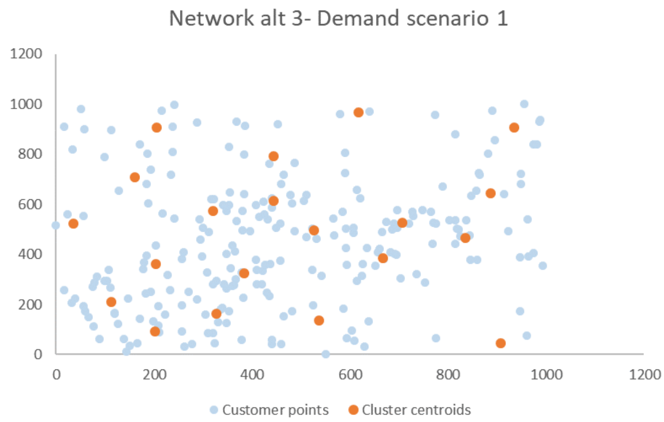
A. PRICES AND SPECIFICATIONS OF CARGO VEHICLES USED IN NETWORK ALTERNATIVES:

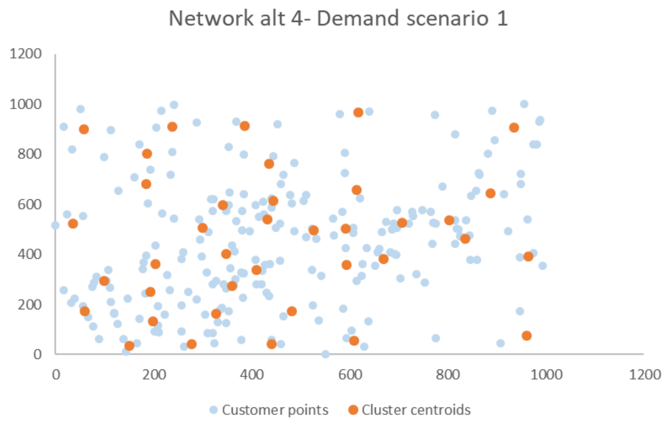
Type, features, specifications	**Diesel delivery van**	**Battery Electric delivery van**	**LEFV**	**Diesel box truck**	**Electric box truck**
Vehicle type	Nissan NV200	Nissan eNV200	NA	Sprinter	eSprinter
Purchasing price	15652 €	34028 €	5200 €	22349 €	52000 €
Insurance cost/ year	610 €	1088 €	166 €	687 €	1664 €
Road tax /year	312 €	0	0	312 €	0
Vehicle mileage	0.12 L/km	0.153 kWh/km	0.06 kWh /km	0.14 L/km	0.31 kWh /km
Maintenance cost	0.0205 €/km	0.0096 €/km	0.0048 €/km	0.0432 €/km	0.020 €/km
Driving range	-	145 km	70 km	-	-
Cargo capacity	4200 L	4200 L	850 L	10800 L	10800 L

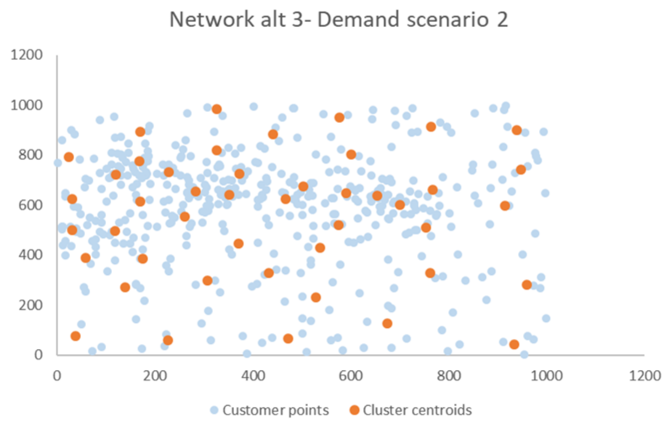
B. Characteristics of clusters for network alternative 3 in demand scenario 2 .

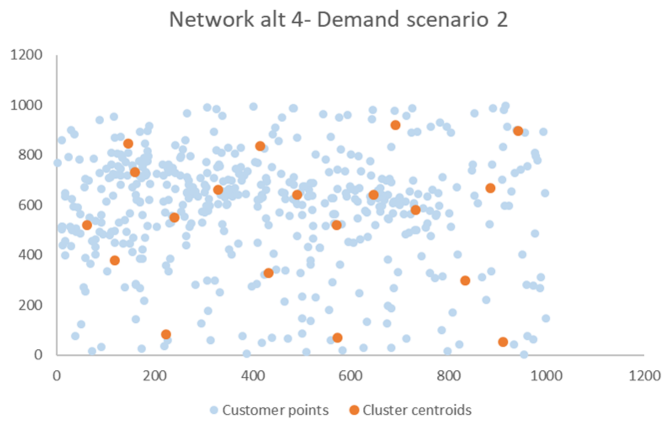
Clusters centroids		Q_j (number of customers)	N_j (number of LEFV trips)
X coordinate	**Y coordinate**		
326	**818**	11	1
171	**615**	11	1
538	**428**	10	1
675	**128**	9	1
768	**660**	9	1
308	**298**	5	1
38	**76**	4	1
916	**597**	9	1
175	**386**	9	1
24	**791**	7	1
139	**270**	7	1
472	**66**	12	1
763	**327**	9	1
959	**282**	8	1
529	**231**	6	1
577	**949**	8	1
327	**985**	5	1
441	**883**	7	1
934	**42**	8	1
948	**742**	10	1
371	**447**	6	1
504	**676**	13	1
227	**60**	7	1
262	**554**	18	1
433	**330**	8	1
939	**901**	9	1
284	**656**	15	1
58	**388**	7	1
118	**496**	18	1
753	**510**	12	1
591	**648**	13	1
228	**732**	18	1
121	**722**	20	1
700	**602**	19	1
576	**520**	12	1
655	**637**	20	1
168	**777**	15	1
764	**912**	11	1
601	**803**	10	1
353	**642**	16	1
467	**625**	19	1
31	**499**	14	1
372	**727**	20	1
170	**895**	9	1
31	**623**	7	1

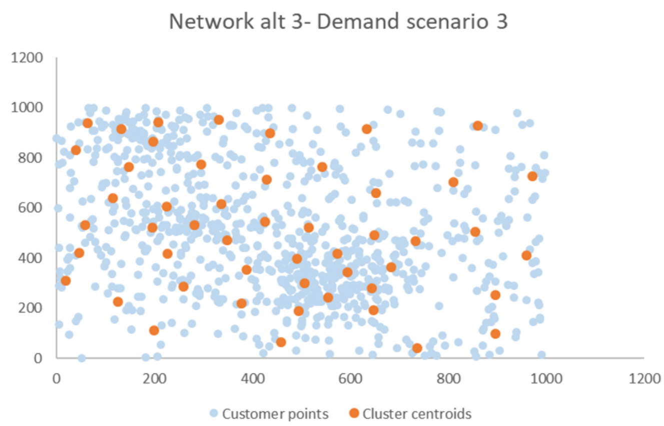
C. Clustering outputs for network alternative 3 and 4 in demand scenarios.

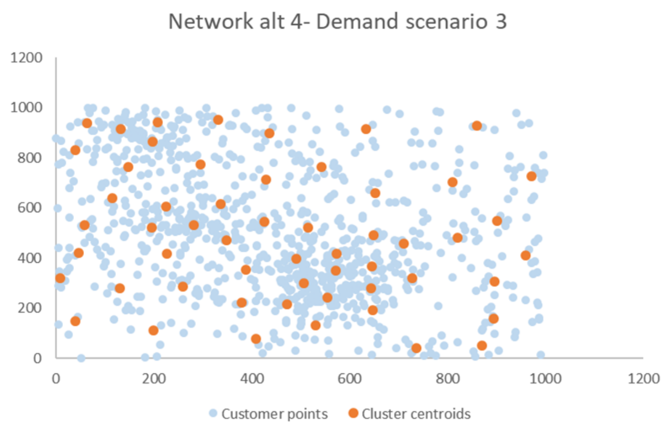




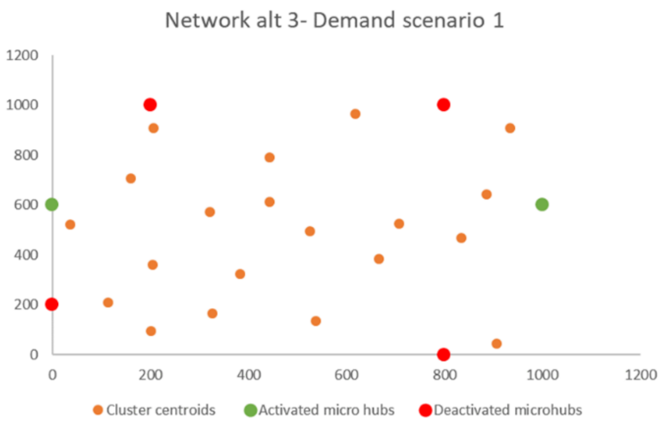


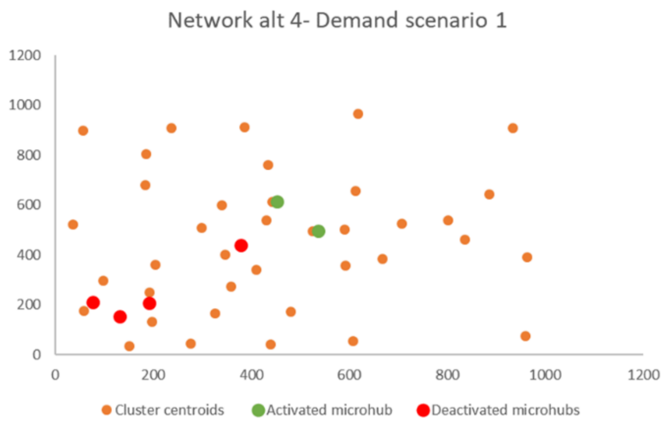


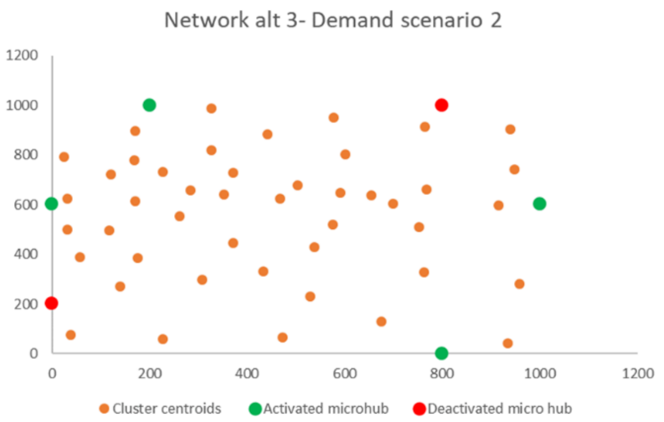


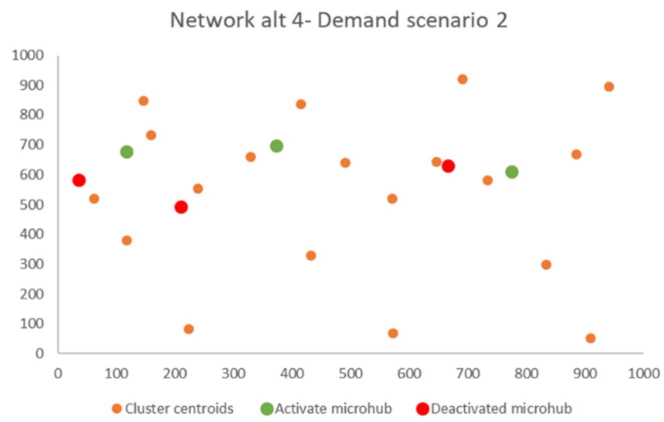


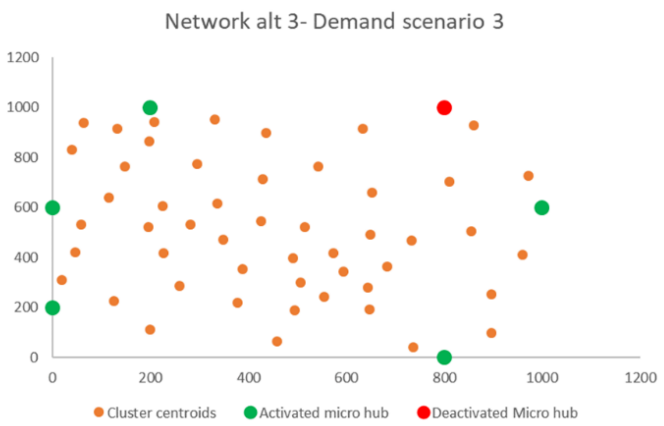
D. LRP model outputs for network alternatives 3 and 4 with demand scenarios.

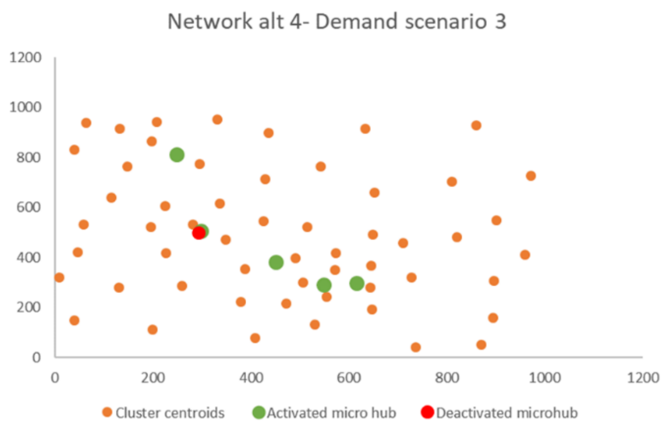












Decision support tool for performance evaluation of urban transshipment networks with electric freight vehicles in low emission zone

A.Nallapeta,

TPM, Delft University of Technology, Delft, The Netherlands

Abstract- Urban transshipment network is a transshipment solution for last-mile distribution in dense metropolitan regions. In this network, a set of micro hubs located in the urban areas are used for deconsolidating shipments and transferring them from high capacity vehicles to light freight vehicles that eventually deliver to customer locations. Due to the shorter distances between the micro hubs and final customers, these networks can be combined with light electric freight vehicles with limited driving ranges to deliver shipments from micro hubs networks. Thus, logistics service providers can potentially adopt these networks for complying with new low emission zone policies that restrict diesel cargo vehicles to enter dense urban regions. However, before deciding to adopt these new networks over existing conventional ones, it is imperative to assess the performance of these networks towards achieving overall business objectives. Although optimization models can be used for the evaluation process, the existing models that can be used for urban transshipment networks are computationally complex, causing their limited application to real-life contexts. Thus, this research presents a new continuous approximation-based model in the form of a support system for LSP to evaluate the performance of urban transshipment networks in a simpler aggregate manner. The application of the support system to a synthetic case study revealed that the model was able to provide a feasible solution that was adequate for strategic evaluation and performance of urban transshipment networks was contingent on the density of customer points in LEZ

Index Terms- Transshipment networks, Micro hubs, light electric freight vehicles, low emission zones, performance evaluation

I. INTRODUCTION

Transshipment network is an existing practice in the logistics sector, in which goods are shipped to an intermediate logistics facility called a hub before transporting them to their final destination (Huber et al., 2015). The urban transshipment network is an adaption of the above logistic practice for last-mile distribution in dense metropolitan regions. In this network, a set of micro hubs located in the urban areas are used for deconsolidating shipments and transferring them from high capacity vehicles to light freight vehicles that deliver to customer locations (Merchan et al., 2016). The micro hubs are storage facilities but with a smaller physical footprint dedicated purely for mode shift. Due to the shorter distances between the micro hubs and final customers, these networks can be combined with light electric freight vehicles (LEFV) with limited driving ranges to deliver shipments from micro hubs (Quak, Nesterova, & Van Rooijen, 2016). Recently, municipalities are introducing low emission zone (LEZ) in high-density urban areas to limit access to diesel-powered cargo vehicles (Dablanc & Montenon, 2015). Consequently, logistics service providers (LSP) engaged in last-mile delivery services within these LEZs are compelled to change their existing logistics systems with diesel vehicles. Urban transshipment networks, combined with LEFVs, offer a potential solution for LSPs to perform uninterrupted operations in LEZ as LEFVs usually meet the entry requirements of LEZ. However, before deciding to adopt these new networks over existing conventional ones, private LSPs must assess the performance of these networks towards achieving their strategic business objectives (Gunasekaran et al., 2004).

Performing the evaluation of a logistics network's performance prior any application is complicated because the configuration of the network which affects the overall distribution activity is not known. A configuration of an urban transshipment network is characterized by the size, location, numbers of micro hubs, and fleet sizes of the cargo vehicle fleets employed in the network (Merchan et al., 2016). However, it is apparent that the LSP would consider applying only that configuration which minimizes the costs to the firm (Rybakov, 2017). For this reason, network design optimization models play an essential role, as they can determine the cost-optimal configuration from all possible configurations and analytically reproduce the corresponding distribution activities (Amodeo et al., 2015). In the case of urban transshipment networks, finding cost-optimal configurations is complicated as it involves two interrelated decisions, micro hub location, and vehicle routing. Location routing problems (LRP) model is a specific type of network design optimization model that is capable of coping with the interrelationship mentioned above to determine cost-optimal configurations of urban transshipment networks (Prodhon & Prins, 2014). Nevertheless, the existing LRP models are computationally complex, causing their limited application to real-life contexts (Cuda et al., 2015a). Parsimonious techniques like continuous approximation (CA) have shown to alleviate the complexity of these models, especially at the routing level, to provide near-optimal solutions for large scale problems (Ansari et al., 2018)

This research presents a model-driven decision support tool (DST) that compares the performance of urban transshipment networks with other feasible networks for last-mile delivery services. The performance of the networks is analyzed based on their cost-optimal network configurations. Classic optimization models are adopted for determining cost-optimal configurations of conventional network types, while a new CA-based model is proposed for urban transshipment networks. The DST is presented as a sequential framework, which guides the LSPs to analyze the performance of urban transshipment networks for their last-mile operations. Finally, the proposed DST is applied to a synthetic case study to demonstrate its capabilities.

II. BRIEF LITERATURE REVIEW ON LRP MODELS

In operation research (OR), intermediate logistics facilities such as micro depots, are termed as 'hubs' in operations research. OR models that account for interdependencies between hub location and vehicle routing while finding the optimal network configuration are called as location routing problems (LRP) (Aykin, 1995). In contexts where goods flow occurs in two distinct echelons, such as the cases of urban logistics with micro hubs, the LRP is termed as a Two-Echelon LRP (2E-LRP) (Drexl & Schneider, 2015). The first echelon goods flow is between faraway storage depots to intermediate micro hubs, whereas the second echelon deals with goods delivery from micro hubs to customer locations. 2E-LRP aims at finding the locations for hubs among candidate locations and simultaneously determine the routes of the vehicle fleet at both echelons, such that the value of the objective function is either minimized or maximised (Crainic et al., 2010).

Boccia et al. (2010) formalized the 2E-LRP, and later, Crainic et al. (2011) proposed three multi integer formulations for the 2E-LRP and solved them using a commercial solver. The exact approach was capable of solving small instances consisting of not more than 25 customers, and when used on more extensive problems, the solution gaps were as high as 25%. Contardo et al. (2012) proposed a two index multi integer linear 2E-LRP formulation that was strengthened by a family of inequalities. The authors developed a branch and cut algorithm to solve the model on CPLEX. This method could solve the problem with 50 customers and is recognized as the best in a class of exact methods for solving a 2E-LRP (Contardo et al., 2013). The inability to solve realistic large 2E-LRPs with exact methods is because these problems are NP-hard as it constitutes of two other NP-hard problems; facility location and vehicle routing problems (Cuda et al.,2015).

Since exact methods alone are incapable of solving large 2E-LRPs, the majority of researchers have drawn focus to (meta-) heuristic methods. Boccia et al. (2010) proposed a tabu search method that decomposes the 2E-LRP problem into two subproblems: facility location problems (FLP) and vehicle routing problem (VRP) (at both the echelon). A similar approach was adopted by Gao et al. (2016), where they used K means clustering and Ant colony optimization for solving an FLP and VRP, respectively. Nugen et al. (2012a, 2012b) propose two heuristic procedure greedy randomized adaptive search procedure (GRASP) and a multi-start iterated local search (MS-ILS). Contardo et al. (2012) proposed an adaptive large-neighborhood search (ALNS) meta-heuristic to find, in reasonable times, good quality solutions for instances with 200 customers. However, in real-life applications, the size of LSP operating within an entire city corresponds to bigger problem instances than above. Notably, the routing aspect, which involves many small vehicles and hundred of customers per square kilometer, will render the corresponding 2E-LRP intractable (Cuda et al. 2015).

Winkenbach et al. (2016), in cooperation with French PO- 'La Poste,' demonstrated a different approach to resolve a 2E-LRP model by using a continuous approximation (CA) techniques. The routing costing in the second echelon was approximated using route length estimation formulas instead of finding the explicit routes of vehicles in the second echelon through VRP formulations. The authors argue for this method as routing decisions in operational levels play a secondary role as LRP is used for strategic network design. However, the approach ignores the spatial distribution of the customer points by dividing the entire problem instance equally to rectangular spaces with uniform distribution of customers. This assumption could result in more travel distances and consequently increase fleet sizes of electric vehicles, which have limited driving ranges. To our best knowledge, aside from Winkenbach et al., (2016), studies adopting CA approaches to solve 2E-LRP have not been conducted in the past.

III. METHODOLOGY

This section explains the model-driven DST, based on the works of is developed to help LSPs virtually evaluate urban transshipment networks for their last-mile operations in the LEZ region. It consists of several distinguishable steps that guide the LSPs to evaluate, as presented in Figure 1. The required input data for each step in the DST is extracted from information sources either internally or externally available to the LSP. Upon clearly defining the current network and alternative networks, a set of optimization models determine their cost-optimal network configurations that fulfill the generated demand scenario with minimum TLC. These cost-optimal configurations, later, serve as the basis for performance comparison between network alternatives.

A. Demand scenario:

The first step in DST deals with generating demand scenarios to reproduce either the current or future daily service needs of LSP inside a LEZ of interest. The demand scenario is created using the data on customers (demands and locations) located inside a LEZ on a typical working day. Alongside the spatial distribution of customers, the depot location is fixed in the demand scenario.

B. Define Network alternative:

The following step in the DST involves defining different logistics networks that alternatively can be adopted by the LSP to fulfill the above-defined scenario. These include the currently employed network as well as three other possible substitute networks that either use electric vehicles and transshipment facilities to deliver customers within the LEZ. The structures of these networks are generalized for the application of the DST, as shown in Table 1. Various types of functional elements are being employed in network alternatives. These elements include a range of cargo vehicles (diesel or electric vans, LEFVs, diesel or electric trucks), and micro transshipment facilities. Based upon the prices and specifications of all functional elements, the list of operating costs and constraints for each of these functional elements must be defined, as shown in Table 2.

Table 1: Network alternatives

Network alternative 1	Distribution strategy: Single echelon distribution system Vehicle fleet: Homogeneous diesel vans
Network alternative 2	Distribution strategy: Single echelon distribution system Vehicle fleet: Homogeneous battery-electric cargo vans Vehicle charging strategy: overnight charging
Network alternative 3	Distribution strategy: Two echelon distribution system Vehicle fleets: Homogeneous LEFVs and diesel box trucks Logistics facilities: Micro hubs Electric vehicle charging strategy: overnight charging
Network alternative 4	Distribution strategy: Two echelon distribution system Vehicle fleets: Homogeneous LEFVs and Electric box trucks Logistics facilities: Micro hubs Electric vehicle charging strategy: overnight charging

Table 2: Operating costs and constraints of network elements

<table>
<tr><th>Functional elements</th><th>Operating constraints</th><th>Operating Costs</th></tr>
<tr><td>Diesel vans</td><td>- Cargo capacity</td><td>Daily depreciation cost (incl. insurance, road tax)
Daily labour costs/vehicle
Running cost of the vehicle (incl. fuel costs, maintenance)</td></tr>
<tr><td>Battery electric vans</td><td rowspan="2">- Cargo capacity
- Driving range</td><td rowspan="2">Daily depreciation cost (incl. insurance, road tax)
Daily labour costs/vehicle
Running cost of the vehicle (incl. fuel costs, maintenance, surcharge for charging)</td></tr>
<tr><td>LEFV</td></tr>
<tr><td>Micro hub</td><td>Storage capacity (L)</td><td>Daily operating cost (€) (incl. rent and Staff)</td></tr>
<tr><td>Diesel box trucks</td><td>- Payload capacity (L)</td><td>Utilization cost (€/km) (incl. depreciation, labour,</td></tr>
</table>

		fuel)
Electric box trucks	- Payload capacity (L) - Driving range	

C. Network optimization module:

A set of two different combinatorial optimization models is adopted for determining the cost-optimal configurations of network alternatives. Finding the cost-optimal configurations of the network alternative 1 and 2 implies determining fleet sizes of delivery vans that minimizes the TLC. A three-index flow formulation proposed by Baldacci et al. (2004) is employed to model alternatives 1 and 2 into distinct CVRPs with TLC as the objective function. The model description and formulation not explained in the paper. Finding the cost-optimal configurations of network alternatives 3 and 4 implies determining the locations, numbers, and sizes of micro hubs and vehicle fleet sizes that will minimize the daily TLC and satisfy the demand scenario in question. a new CA-based two-step optimization method with daily TLC as the objective function is proposed as a substitute for the traditional 2E-LRP models. This model is henceforth called the approximated 2E-LRP model. The proposed method reduces the computational complexity by decomposing a single complex optimization problem into two relatively simpler optimization subproblems. The clustering problem is the first subproblem, which aims to create a set of compact customer clusters, Such that every customer point from the demand scenario is encompassed by one cluster. Upon forming these clusters, the distance traveled by LEFVs, total customer demand, and LEFV trips required are determined for each of these created clusters. Next, the location fleet size problem (LFP) involves allocating these parameterized clusters to a set of prospective micro hub locations and determining the fleet size of the vehicles in the network. A set of notations shown in Table 3:Clustering model notation is used in explaining the formulation of the clustering model as shown below,

Table 3:Clustering model notation

$\boldsymbol{i,j}$	$\in \{1 \ldots\ldots v\}$: Set of customer points
$\boldsymbol{P_j}$	Binary decision variable indicating if a customer j is selected as a centroid point
$\boldsymbol{A_{ij}}$	Binary intermediate variable indicates if a customer i is assigned to a centroid point j
$\boldsymbol{N_j}$	Binary decision variable indicating the number of LEFVs trips required to service each cluster j
$\boldsymbol{n_c}$	Number of clusters
$\boldsymbol{C^d}$	The variable cost of LEFV
$\boldsymbol{C^v}$	The fixed cost of LEFV per trip
$\boldsymbol{Q^{Hub}}$	The storage capacity of micro hub
$\boldsymbol{Q^{LEFV}}$	The payload capacity of LEFV
$\boldsymbol{d_{ij}}$	Distances between customer i and j

Minimize $\sum_{j=1}^{v}\sum_{i=1}^{v} \boldsymbol{d_{ij}.A_{ij}.C^d} + \sum_{j=1}^{v} \boldsymbol{N_j.C^v}$ (2)

Subject to

$A_{ij} \leq P_j, \quad \forall i.j \in V,$ (2.1)

$\sum_{j=1}^{v} P_j = n_c,$ (2.2)

$\sum_{j=1}^{v} A_{ij} = 1, \quad \forall i \in V,$ (2.3)

$\sum_{i=1}^{v} A_{ij}.D_i \leq Q^{Hub}, \quad \forall j \in V,$ (2.4)

$\sum_{i=1}^{v} A_{ij}.D_i \leq N_j * Q^{LEFV}, \quad \forall j \in V,$ (2.5)

$A_{ij}, P_j \in [0,1], \quad N_j \in R, \quad \forall i,j \in V,$ (2.6)

The model aims to form customer clusters by finding the values of variables P_j, A_{ij} and N_j such that the objective function (2) is minimized. Constraint (2.1) ensures that a customer is allocated to only a centroid customer. Constraint (2.2) ensures that the total number of centroids is equal to the input number of clusters n_c. Constraint (2.3) ensures that every customer is assigned to one centroid. Constraint (2.4) restricts the total demand of a cluster to no exceed beyond the micro hub's capacity. Constraint (2.5) ensures that enough LEFV trips required at each cluster are adequate based on payload capacity. Constraints (2.6) are binary and integer constraints for the variables. The optimal clusters thus obtained from the clustering model is parameterized before inputting them to the next model. Since the centroid is unique to a customer cluster, Each cluster is represented by their respective centroid j an enclosed in a set $C \subseteq V$ with a cardinality n_c. A list of parameters is calculated for every cluster $j \in C$, as shown in Table 2.

Table 4: Parameterization of optimum clusters

$\boldsymbol{N_j}$	Number of LEFV trips required to service the customer cluster j
$\boldsymbol{Q_j}$	The total customer demand for cluster j
$\boldsymbol{A_j}$	The area of minimum area rectangle (MAR) bounding all customers in cluster j
$\boldsymbol{Td_j}$	The approximate total distance travelled by N_j LEFVs within the cluster j $= k * \frac{n_j - N_j}{n_j} * \sqrt{n_j . A_j}$ (k is the local tour parameter given as input)

With the parameterized clusters as inputs, the LFP must take the following decisions concurrently: (1) select location for a micro hub and its size (2) allocate every parameterized cluster to one of these activated micro hub locations, (3) determine LEFV fleet sizes at each activated micro hub location, (4) determine the routes of trucks in the first echelon. An integer programming model based on the 2E-LRP model of Crainic et al., (2011) and facility location and allocation model of Tragantalerngsak et al. (2000) is proposed to solve the above LFP. A set of notations shown in Table 5: LRP model notation is used in explaining the formulation of the clustering model as shown below,

Table 5: LRP model notation

$\boldsymbol{C}$	$\subseteq \{1 \ldots \ldots j\}$: cluster set from clustering model
$\boldsymbol{U}$	$\{1 \ldots \ldots h/l\}$: set of prospective micro hub locations
$\boldsymbol{P}$	$\{1 \ldots \ldots k\}$: set of homogeneous box trucks
$\boldsymbol{W_h}$	Binary decision variable denotes if a micro hub h is activated
$\boldsymbol{X_{jh}}$	Binary intermediate variable denotes if a cluster j is assigned to a micro hub location h
$\boldsymbol{M_h}$	Integer decision variable denoting LEFV fleet size at micro hub location h
$\boldsymbol{Z_{khl}}$	Binary decision variable denoting if a box truck k is used to move bundled packages between micro hubs h and l , where $h \neq l$
$\boldsymbol{D_h}$	Integer intermediate variable denoting total distance travelled by M_h LEFVs from micro hub h to serve all clusters assigned to it
$\boldsymbol{Q_h^{hub}}$	Integer intermediate variable denoting the total demand of all customers assigned to micro hub h
$\boldsymbol{F^h}$	The operating cost of a micro hub per day
$\boldsymbol{C^{LEV}}$	The fixed cost of LEFV per day
$\boldsymbol{C^d}$	The variable cost of LEFV
$\boldsymbol{C^T}$	The utilization cost of the box truck (ICE /electric)
$\boldsymbol{D_{hl}}$	The distance between hubs h and l
$\boldsymbol{d_{jh}}$	The distance between centroid point of cluster j and micro hub h
$\boldsymbol{B.R_{LEV}}$	The battery range of LEFV
$\boldsymbol{Q^{Hub}}$	The capacity of the micro hub
$\boldsymbol{Q^1}$	The payload capacity of the box truck (ICE /electric)
$\boldsymbol{Td_j}$	LEFV travel distances within customer cluster j from clustering model
$\boldsymbol{N_j}$	Number of LEFV trips required for each cluster j from clustering model
$\boldsymbol{Q_j}$	The Customer demand for cluster j from clustering model

Minimize:

$$\sum_{h=1}^{v} \boldsymbol{W_h}.\boldsymbol{F^h} + \sum_{h=1}^{v} \boldsymbol{C^{LEV}}.\boldsymbol{M_h} + \sum_{h=1}^{v} \boldsymbol{C^d}.\boldsymbol{D_h} + \sum_{k=1}^{p} \sum_{h=0}^{v} \sum_{l=0\ h\neq l}^{v} \boldsymbol{C^T}.\boldsymbol{D_{hl}}.\boldsymbol{Z_{khl}} - \sum_{l=1}^{v} \boldsymbol{C^T}.\mathbf{2}.\boldsymbol{D_{0l}}.|\boldsymbol{W_l} - \mathbf{1}| \quad \mathbf{(3)}$$

- $X_{jh} \leq W_h$ $\quad \forall j \in C, h \in V \setminus \{0\}$ (3.2)
- $\sum_{h=1}^{v} X_{jh} = 1$ $\quad \forall j \in C$ (3.3)
- $D_h = \sum_{j \in C} X_{jh}.[\,Td_j + 2(\,d_{jh}.N_j)\,]$ $\quad \forall\ h \in V \setminus \{0\}$ (3.4)
- $M_h.Br_{LEV} \geq D_h$ $\quad \forall\ h \in V \setminus \{0\}$ (3.5)
- $Q_h^{hub} = \sum_{j \in C} X_{jh}.Q_j$ $\quad \forall h \in V \setminus \{0\}$ (3.6)
- $Q_h^{hub} \leq Q^{hub}$ $\quad \forall h \in V \setminus \{0\}$ (3.7)
- $\sum_{k=1}^{p} \sum_{h=0\ h\neq l}^{v} Z_{khl} = 1$ $\quad \forall l \in V \setminus \{0\}$ (3.8)
- $Z_{khl} \leq W_l$ $\quad \forall h, l \in V \setminus \{0\}, h \neq l, k \in P$ (3.9)
- $\sum_{l=1}^{v} Z_{k0l} = 1$ $\quad \forall k \in P$ (3.10)
- $\sum_{h=0\ h\neq l}^{u} Z_{khl} = \sum_{h=0\ h\neq l}^{u} Z_{klh}$ $\quad \forall l \in V, k \in P$ (3.11)
- $\sum_{h=0}^{u} \sum_{l=1\ h\neq l}^{u} Q_l^{hub}.Z_{khl} \leq Q^1$ $\quad \forall k \in P$ (3.12)
- $\sum_{k=1}^{p} \sum_{h \in S} \sum_{l \in S\ h\neq l} Z_{khl} \leq |S| - 1$ $\quad \forall S \subseteq V \setminus \{0\}$ (3.13)

The objective function (3.1) represents that daily TLC. It comprises of three main cost components, the total daily fixed operating cost of micro hubs, total daily fixed and variable cost of LEFVs, and total utilization cost of box trucks in the first echelon of goods transport. For finding the total utilization costs of box trucks, the costs of unnecessary visits to deactivated micro hubs by the additional box trucks are invalidated. This approach is adopted to avoid nonlinear constraints and objective functions. Constraint (3.2) ensures that a customer cluster j is assigned to micro hub location h (X_jh=1) only if micro hub location h is activated (W_h=1). Constraint (3.3) makes sure that every cluster is assigned to only one micro hub location. Constraints (3.4) and (3.5) ensures that, for each micro hub h, the total battery range of M_h number of LEFVs is at the least equal to the total distance required to service customer clusters assigned it. Constraints (3.6) and (3.7) ensures the storage capacities of micro hubs are not violated. Constraint (3.8) is a flow constraint in the first echelon, which ensures that every micro hub (activated /deactivated) is visited by a box truck form either the depot or another micro hub. Constraints (3.9) will ensure that the box truck can serve multiple micro hubs on a trip only if they are activated. Constraints (3.10) ensures that every truck k starts its trip from the depot. Constraint (3.11) guarantees that the number of box trucks arriving is equal to those leaving at every micro hub and depot. In this way, Constraints 3.8, 3.9, 3.10, and 3.11 make sure that the activated micro hubs are visited by a vehicle either from the depot or another activated micro hub whereas, deactivated micro hubs are visited by individual box truck from the depot. The costs of these dedicated routes to deactivated micro hubs from the depot are deducted from the total utilization cost of box trucks, as seen in the objective function. In this way, only the costs of utilizing box trucks for activated micro hubs are considered in TLC computation. Constraint (3.12) makes sure that the payload capacity of box trucks is not violated, and constraint (3.13) is a sub route elimination constraint for the first echelon.

To model the proposed approximate 2E-LRP corresponding to alternatives 3 and 4, both the clustering problem and the location and fleet problem related to these network alternatives must be individually modeled using the formulations shown above. The values of the model parameter values are either be assumed (for the number of clusters n_c) or derived based on the defined operating costs and constraints of functional elements (LEFVs, micro hubs, and box trucks). However, due to this sequential data flow between the models, the value for the number of clusters n_c inputted exogenously in the clustering model indirectly influences the outputs of the location and fleet size model. Thus, it is essential to find the ideal input values of the parameter n_c. For this reason, a solution algorithm (as illustrated in **Error! Reference source not found.**) is built to iteratively solve the above models (in the sequential order) for a range of input values of n_c.

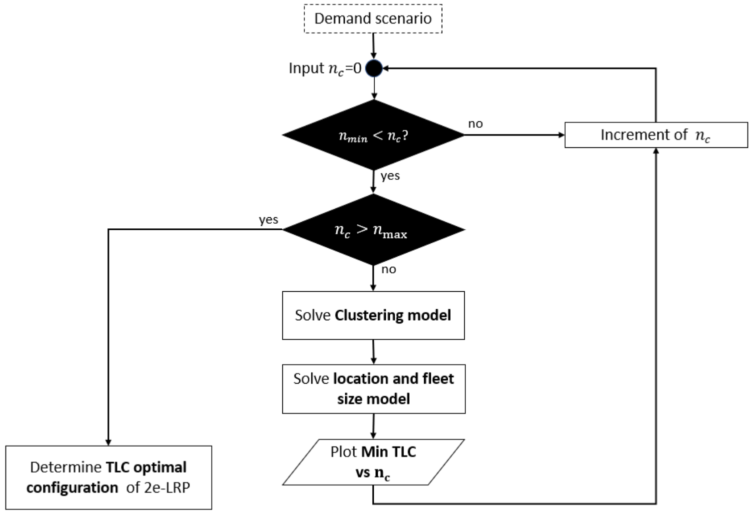


Figure 1:Iterative sequential algorithm

D. Network performance

The network's performance is measured using KPI, which can be classified into four categories, namely economic, environmental, operational KPIs. All the different KPIs with which the network's performance is analyzed are explained in the following sections. From an economic point of view, two KPIs are analyzed; namely, *daily TLC* and the *average cost per parcel*, the daily total logistics cost of a network alternative is equivalent to the minimized value of TLC corresponding to the cost-optimal configuration of networks. Whereas, the average cost per parcel is estimated using the below formulae:

- $\boldsymbol{The\ average\ cost\ per\ unit\ delivered} = \frac{daily\ total\ logistics\ cost\ (TLC)}{number\ of\ parcels\ delivered}$

From an environmental perspective, network alternatives are compared based on the total Well-to- Wheel (WTW) CO2 emissions from freight vehicles. This KPI involves two sub-components, Well-to-Tank (WTT), and Tank- to-wheel (TTW) emissions. The former accounts for the CO2 emissions discharged during the production of fuel or electricity, whereas the latter includes tailpipe discharge from vehicle fleets. The following set of formulas are used to measure the value of total WTW CO2 emissions:

- $$\boldsymbol{Total\ WTW\ CO_2\ emissions} = Total\ WTT\ CO_2\ emissions\ all\ vehicles\ modes + Total\ TTW\ CO_2\ emissions\ all\ vehicles\ modes$$

Where,

- $$WTT\ CO_2\ emissions\ per\ vehicle\ mode = Total\ distances\ traveled\ per\ vehicle\ mode \times Vehicle's\ energy\ consumption \times CO2\ emissions\ per\ litre\ of\ diesel\ or\ kWh\ of\ electricity\ produced$$

- $$TTW\ CO_2\ emissions\ per\ vehicle\ mode = Distances\ traveled\ per\ vehicle\ mode \times Vehicle's\ energy\ consumption \times CO2\ emissions\ per\ liter\ of\ diesel\ or\ kWh\ of\ electricity\ consumed$$

For the above formulas, Total distance traveled per vehicle mode is obtained as outputs from network optimization models. Values for vehicles' energy consumption is equivalent to fuel or energy consumption of diesel and electric vehicles used in network alternatives (from defined vehicle specifications). Whereas, the average values for CO2 emissions per liter of diesel and kWh of electricity produced or consumed must be inputted exogenously by the LSP.Additionally, from an environmental perspective, It is essential to check if an LSP would consider shifting from the conventional network alternatives with diesel vehicles to sustainable network alternatives with electric vehicles. Therefore, a new qualitative KPI called the likelihood of adoption is defined to predict the chances of an LSP to adopt network alternatives 2, 3, and 4 from network alt 1. Considering that network alt 1 is the current network that uses diesel vans in LEZ, the likelihood of adoption is measured explicitly for network alt 2, 3, and 4, which employ either LEFVs or electric box trucks. This KPI is measured based on two parameters, minimum LEZ penalty on diesel vans to shift from alternative 1 (MPDS) and the actual LEZ penalty as levied by the municipality.MPDS is determined using the outputs of the network optimization models, whereas actual LEZ is exogenously inputted based on the context. The formulas used to calculate the parameters and the KPI are shown below.

- $\textbf{Likelihood of adoption} = \text{HIGH},\ \text{if MPDS} < \text{actual LEZ penalty}$

$$\text{LOW},\ \text{if MPDS} > \text{actual LEZ penalty}$$

Where,

$$MPDS = \frac{Daily\ TLC - Daily\ TLC\ of\ network\ alt\ 1}{The\ optimal\ fleet\ size\ of\ diesel\ vans\ for\ network\ alt\ 1}$$

The values for Daily TLC and optimal fleet sizes of diesel vans for network alt 1 are obtained from the outputs of network optimization models. Whereas, the actual LEZ penalty is as an input parameter. Considering that time is very crucial in last-mile deliveries, two KPIs, namely total operation time and average service time per customer, are used as KPI for measuring the performance of network alternatives. Measuring these KPI will show if these new networks would result in more or reduced time to perform deliveries to customer locations.

- $\boldsymbol{Total\ Operation\ time\ per\ day} = Total\ travel\ time\ all\ vehicle\ modes + Total\ handling\ time\ all\ vehicle\ modes$

  Where,

  - $Travel\ time\ per\ vehicle\ mode = \frac{distance\ traveled\ per\ vehicle\ mode}{average\ speed}$

  - $Handling\ time\ per\ mode = Total\ delivery\ time\ at\ customer\ reception\ points + handling\ time\ at\ micro\ hubs$

- $\textbf{Average service time per customer} = \frac{Total\ operation\ time\ per\ day}{Number\ of\ customers\ per\ day}$

To calculate the above formulas, Distances traveled by the vehicles are obtained as outputs from network optimization models. LSPs must exogenously specify the values of the average speed of vehicles, delivery time per customer, and Handling time at micro hubs for LEFVs and box trucks based on their business.

APPLICATION

A. Generated demand scenario

Demand scenarios are generated using the set of VRP benchmark instances by Uchoa et al. (2017). From this set, three problem instances with 260, 500, and 950 PODs are specially selected, such that the density of PODs linearly increases across the instances. Meaning that the area in which PODs are enclosed remains the same, but the number of customer points increases nearly doubles (=1.9) across instances. Representing every POD in these instances as one customer points, three different demand scenarios are created, as shown in Fig 2. The service is limited only to package delivery and each customer point has a demand for one package. All parcels are assumed to be of the size 42L. The value is based on the average package size considered in Lee et al. (2019a).The demands of all customers in the scenario are assumed to be fulfilled within one operational day.The travel distance between any two points in the scenarios is measured in the Euclidian distance metric with each metric unit equivalent to 10 meters. This value is based on the estimated average distance per parcel in Clarke & Leonardi (2017). A virtual square area encompassing all customer points is used to represent the LEZ in all three demand scenarios, as shown in **Error! Reference source not found.**. The length of the LEZ area is set as 10km and retained the same across the scenarios.The location of the depot is fixed at 20km distance from the boundary of LEZ in all three scenarios. This length is based on the average distances between the depot and the first delivery stop in case studies used by Clarke & Leonardi (2017).

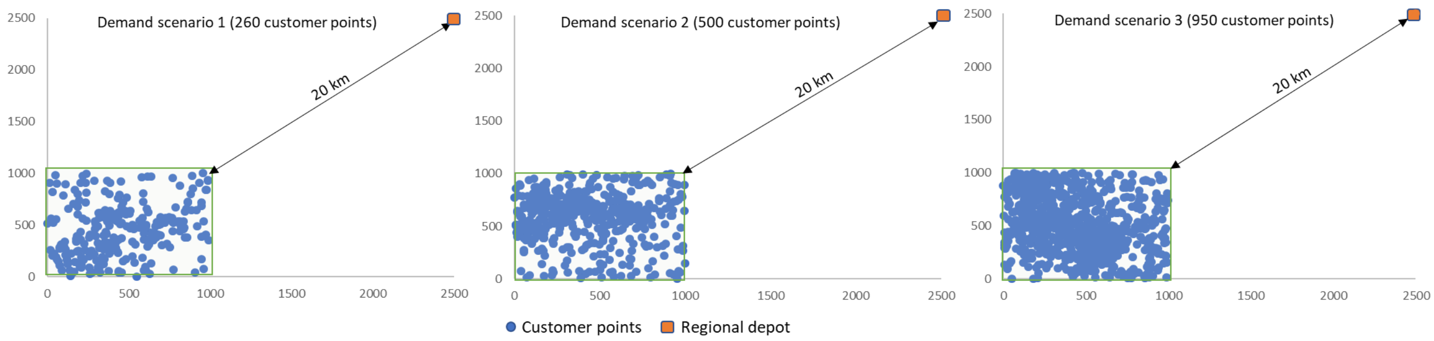


Figure 2: Generated demand scenario

For network alternative types 3 and 4, prospective locations where micro hubs can be established must be specified alongside customer points in the demand scenario. From these locations, the proposed solver algorithm then activates the locations of the micro hubs. Six arbitrary sites on the periphery of the LEZ are selected to serve as prospective micro hub locations for alternative type 3. These potential hub locations are retained the same across all demand scenario. On the other hand, the six random sites from dense regions are selected as prospective hub locations for network type 4.

B. *Define operating cost and constraints of functional elements*

To simulate realistic urban logistic network, the cargo vehicle variants analyzed within the Panteia's total cost of ownership (TCO) model are selected for application within the network alternatives. The operating costs and constraints are derived using information database, calculation procedures and parameters adopted within the TCO model, as shown in Table 6.

Table 6: Operating costs and constraints of functional elements in network alternatives

Network components	**Costs and specifications of network elements**	**Calculation procedures**
Diesel vans (for alt 1)	• Daily depreciation cost = 9.64 € • Daily labour costs/vehicle= 120 € • Running cost of the vehicle =0.18 €/km • The cargo capacity of the vehicle = 4200 L	• The daily depreciation cost of a vehicle is calculated as {Acquisition costs - Resale price} / {ownership period * No. of working days in a year} Assuming, - No. of working days in a year =260 days - Ownership period of vehicles = 8 years - Acquisition costs of vehicle= {Purchasing price + insurance cost and road tax for the ownership period} - Resale price of the vehicle (end of 8 years) = 19% of the purchasing price • The daily labour costs are given by: Hourly wage of vehicle operator * working hours/day Assuming, - Hourly wages of delivery van operator =15 € - Hourly wages of LEFV operator=12€ - Working hours/day for delivery van = 8 hours - Working hours/day for LEFV= 6 hours
Battery electric vans (for alt 2)	• Daily depreciation cost = 17.44 € • Daily labour costs/vehicle= 120 € • Running cost of the vehicle = 0.08 € • The cargo capacity of the vehicle = 4200 • Driving range = 145 km	
LEFV (for both alt 3 and 4)	• Daily depreciation cost = 4.26 € • Daily Labour costs/vehicle= 72 € • Running cost of the LEFV = 0.02 €/km • The cargo capacity of the vehicle = 850 L • Driving range = 70 km	

Diesel box trucks (for alt 3)	▪ Utilization cost = 0.87 €/km ▪ The cargo capacity = 10800 L	• The running cost of vehicle is given by: {Vehicle mileage* Energy price} + Maintenance cost Assuming, - Energy price for all diesel-powered vehicles = 1.3 €/L (diesel price) - Energy price of electric vehicles include electricity price and a surcharge for charging infrastructure ▪ Energy price of electric van/truck = 0.45 €/kWh (20kw charging) ▪ Energy price of LEFV= 0.22 €/kWh (3kw charging) • The utilization cost of a box truck is calculated as {Daily depreciation cost of box truck / average distance travelled} + the running cost of box truck + service cost Assuming, - Service cost = {Hourly wage of box truck operator * Average speed of box trucks} - The average distance travelled by box truck = 50 km - Hourly wages of box truck operator= 15 € - The average speed of box truck = 40 km/h
Electric box trucks (for alt 4)	▪ Utilization cost = 1.09 €/km ▪ The cargo capacity = 10800 L	
Micro hub (for both alt 3 and 4)	▪ The daily operating cost of the micro hub (€) = 115 euros ▪ The storage capacity of micro hub =8500 L	• The daily operating cost of the micro hub is given by: The yearly cost of micro hub / No. of working days in a year Assuming, - The yearly cost of micro hub = 30000 € (incl. rent and Staff) - No. of working days in a year =260 days

Error! Reference source not found.

C. *Model parameters and implementation*

For modeling the CVRP or approximated 2e-LRP models corresponding to network alternatives, the values of the model parameters are estimated based on the above-defined operating costs and constraints of network elements. Since both network alternatives 1 and 2 are modeled into a CVRP model, values of their corresponding model parameters are listed together in Table 7. Similarly, the parameter values used for modeling the approximated 2E-LRP model (clustering model and cluster allocation models) corresponding to alternatives 3 and 4 are listed in Table 8. The value of local tour parameter for demand scenario are set as shown in Table 9 and the value of n_{max} is set to 95. This value of n_{max} is kept the same across all three demand scenarios. The CVRP model approximated 2E-LRP model, and the iterative solution algorithm is implemented in Python 3.8 and solved using GUROBI on a 1.8 GHz Intel Core i5 processor and 8 GB RAM.**Error! Reference source not found.**

Table 7:Model parameters CVRP

Model parameters	Network alt 1 (diesel vans)	Network alt 2 (battery-electric vans)	Assumption
The fixed cost of the van per day (€) - $\boldsymbol{C}$	129.64	137.44	= Daily depreciation cost + Daily labour costs/vehicle
The variable cost of a van	0.18	0.08	= Running cost of the vehicle

(€/km)- $\boldsymbol{c}$			
The payload capacity of the van (packages)- $\boldsymbol{Q}$	100	100	= The cargo capacity of the vehicle/ size of a package (42 L)
Battery range limit of the electric van (km)- $\boldsymbol{Br}$	N/A	145	= Driving range of a vehicle
Distances between customer i and j - $\boldsymbol{d_{ij}}$	{Euclidean metric} * 10 meters		Based on the defined demand scenario

Table 8:Model parameters approximated 2E-LRP

Model parameters	**Network Alt 3 (LEFV+ micro-hubs+ diesel box trucks)**	**Network Alt 4 (LEFV + micro-hubs+ electric box trucks)**	**Assumption**
The variable cost of LEFV (€/km) -$\boldsymbol{C^d}$	0.02	0.02	= Running cost of LEFV
Fixed cost of a LEFV per trip - $\boldsymbol{C^V}$	76.26	76.26	= Daily depreciation cost of LEFV + Daily labour costs/LEFV
The capacity of micro hub- $\boldsymbol{Q^{Hub}}$	200	200	= The storage capacity of the micro hub/ size of a package (42 L)
The payload capacity of LEFV- $\boldsymbol{Q^{LEFV}}$	20	20	= The cargo capacity of the vehicle/ size of a package (42 L)
The operating cost of a micro hub per day (€)- $\boldsymbol{F^h}$	115	115	= The daily operating cost of the micro hub
The fixed cost of LEFV per day (€/km)- $\boldsymbol{C^{LEV}}$	76.26	76.26	=Daily depreciation cost of LEFV + Daily labour costs/LEFV
The utilization cost of the box truck (€/km)-$\boldsymbol{C^T}$	0.87	1.09	= Utilization cost of box trucks
Battery range of LEFV (km)- **B.RLEV**	70	70	= the driving range of a LEFV
The payload capacity of box truck (packages)-$\boldsymbol{Q^1}$	250	250	= The cargo capacity of the vehicle/ size of a package (42 L)
Distances between hubs h and l (km)-$\boldsymbol{D_{hl}}$	{Euclidean metric} * 10 meters		Based on the assumption in the defined demand scenario (refer section)
Distances between cluster centroid j and micro hub h (km)- $\boldsymbol{D_{jh}}$			
Distances between customer i and j - $\boldsymbol{d_{ij}}$			
Travel distances within customer cluster j (km)-$\boldsymbol{Td_j}$	Outputs from the clustering model		Based on the sequential flow of data in the approximated 2e-LRP model (refer section)
Number of LEFV trips required for each cluster j-$\boldsymbol{N_j}$			
Demand for cluster j- $\boldsymbol{Q_j}$			

Table 9: Value of local tour parameter

Demand scenario	**Value of 'K'**
Demand scenario 1 -260	2.4
Demand scenario 2 -500	2.5
Demand scenario 3 -950	2.45

IV. RESULTS

The results are plotted across all three demand scenarios from the case study to investigate how the KPI values change with customer density. Firstly, a comparison of economic KPIs, namely *daily TLC* and *average logistics cost per parcel*, is discussed, followed by the comparison of CO2 emissions by vehicles under environmental performance. Finally, the comparison of operational and societal KPIs are analyzed

A. Economic KPI comparison:

In Figure 3: Daily TLC, the value of the daily TLC corresponding to the cost-optimal configurations of network alternatives are compared with each other. Additionally, the breakdown of the daily TLC to its fixed and variable cost components is also indicated in this figure.

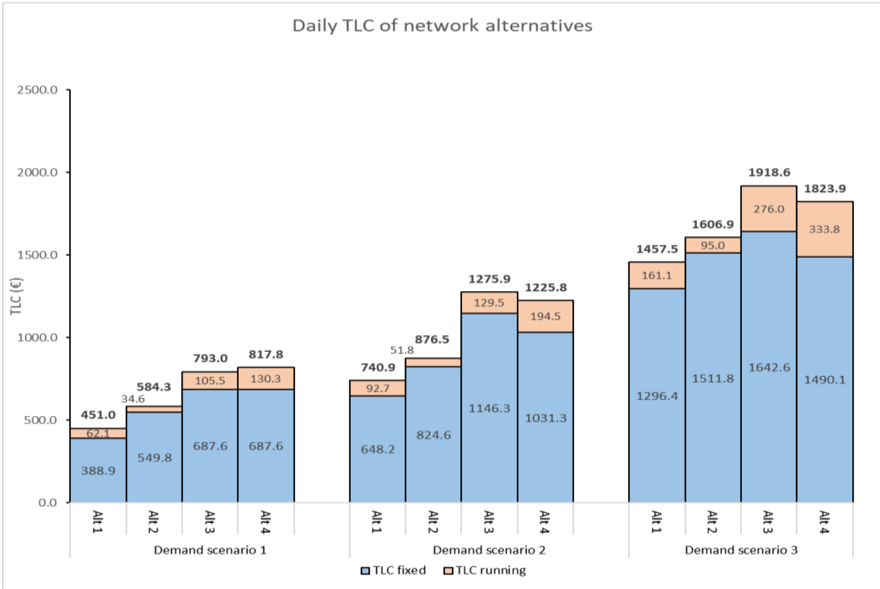


Figure 3: Daily TLC

the average percentage increase in *daily TLC* for network alt 1 and 2 across demand scenarios is relatively higher compared to that of network alt 3 and 4. Doubling the customer density causes *daily TLC* for network alt 1 to increases on an average by 80%, whereas *daily TLCs* of network alt 3 and 4 increase by a value of 50 %. This difference implies that for a demand scenario having a customer density higher than that of considered demand scenario 3, then it is 3 and 4 shows that network alt 4 outperforms alt 3 in the other two scenarios. It is interesting to see that the *average cost per parcel* for network alt 3 and 4 drops significantly across the demand scenarios (refer Figure 4: Average cost per parcel). In demand scenario 1, the *average cost per parcel* for network alt 3 and 4 is much higher than that of networks 1 and 2. However, this gap almost closes in the case of demand scenario 3.

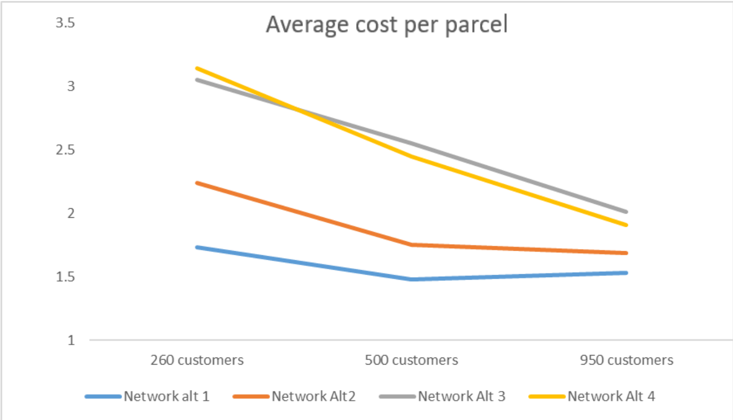


Figure 4: Average cost per parcel

B. Environmental KPI comparison:

Figure 5 compares, across all three demand scenarios, the total WTW CO2 emissions from the vehicle fleets between network alternatives. Additionally, the break down of the total WTW emissions to WTT and TTW emissions are also indicated in Figure 5 11. The diesel vehicles in network alt 1 increases the level of WTW emission levels as they produce a significantly high amount of TTW emissions. In contrast, the WTW emissions from their electric counterparts in network alt 2 are much lesser as they produce zero TTW emissions. In the case of network alt 3, the TTW emissions from the box truck is a significant part of the WTW emissions, and replacing them with electric ones lowers the total WTW emissions drop as seen in the case of network alt 4. It essential to note that WTT emissions are lower when diesel vehicles are used, whereas the TTW emission level is significantly high.

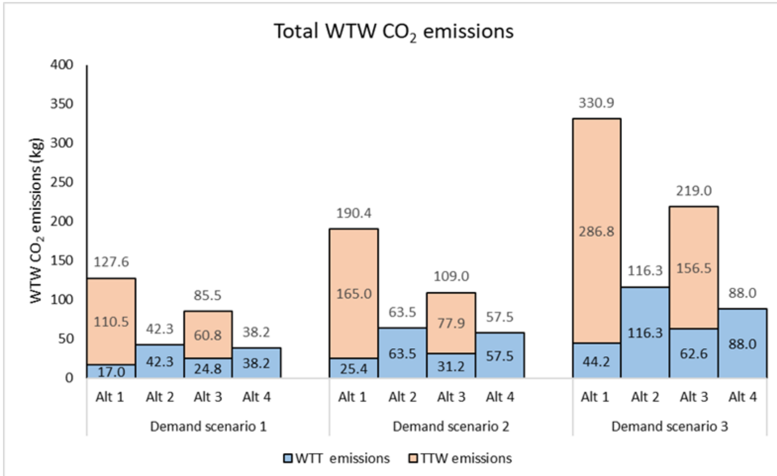


Figure 5:Total WTW CO_2 emissions

Table 10 shows the results of the second environmental KPI- the likelihood of adoption. Alongside the results, The estimated minimum penalty on diesel van to shift from alternative 1 (MPDS) is shown, which is the basis of measuring the likelihood of adoption for network alternatives. In the case of demand scenario 1, The value of MPD for network alt 2 is always much lower than the penalty that the municipality is planning to issue for LEZ entry (95€.). Consequently, the likelihood of adopting network alt 2 is HIGH in all demand scenarios. In contrast, the likelihood of adoption for network alt 3 and 4 to serve demand scenarios 1 and 2 is LOW, because their corresponding MPD is higher than 95€. On the other hand, in the case of demand scenario 3, the likelihood of adoption for network alt 3 and 4 changes to HIGH. Thus, LSP in question can choose to shift from the existing network to either of these alternatives when customer density is high.

Table 10: Likelihood of adopting alt 2,3 and 4

Demand scenarios	***MPS* for network alt 2** *(likelihood of adoption)*	***MPS* for network alt 3** *(likelihood of adoption)*	***MPS* for network alt 4** *(likelihood of adoption)*
Demand scenario 1	44 € **(HIGH)**	122 **(LOW)**	113 **(LOW)**
Demand scenario 2	27€ **(HIGH)**	106 **(LOW)**	96 **(LOW)**
Demand scenario 3	14€ **(HIGH)**	46 **(HIGH)**	36 **(HIGH)**

C. Operational KPI comparison:

Figure 6 compares the *total operation times* for all four network alternatives, along with break down to traveling time and handling time. It is evident that in all three demand scenarios, network alt 1 takes the least time to finish its operations. The handling time of network alt 2 remains the same as network alt 1, but the larger fleet sizes in the former cause a corresponding increase in the travel times. Even though LEFV is significantly fast on urban roads, the additional time required for box truck fleets to unload at the micro hubs increases the *total operation time*. However, it is interesting to see that the vehicle travel time in alternative 4 is lesser compared to network alt 3 when serving demand scenario 3.

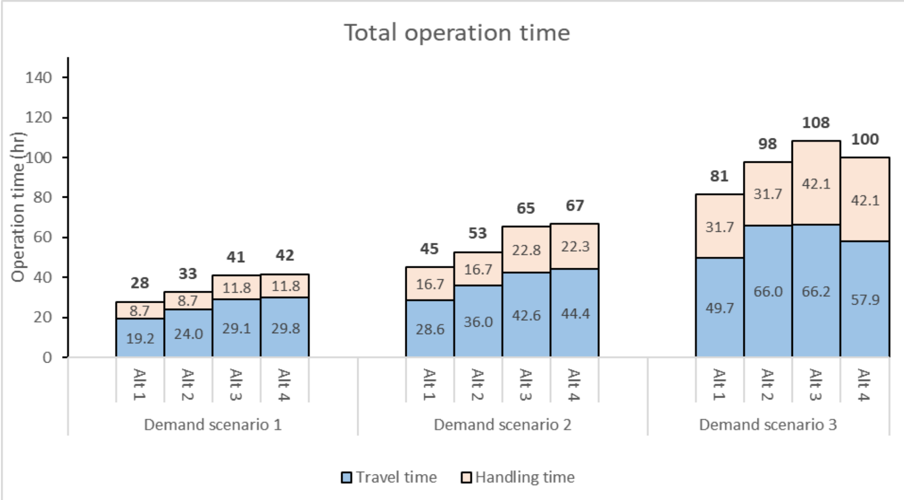


Figure 6: Total operation time

In Figure 7, the *average service time per customer* for network alternatives is plotted across the demand scenarios. Network alternatives 3 and 4 requires, on average, more time to serve a customer compared to network alternatives 1 and 2. However, this gap closes across demand scenarios. As the customer density increases across the demand scenarios, the rate at which this KPI drops is higher for alternatives 3 and 4 compared to alternatives 1 and 2. Notably, the drop is significant for network alternative 4 compared to 3. For demand scenario 3, the value of this KPI is comparable between network alt 4 and 2.

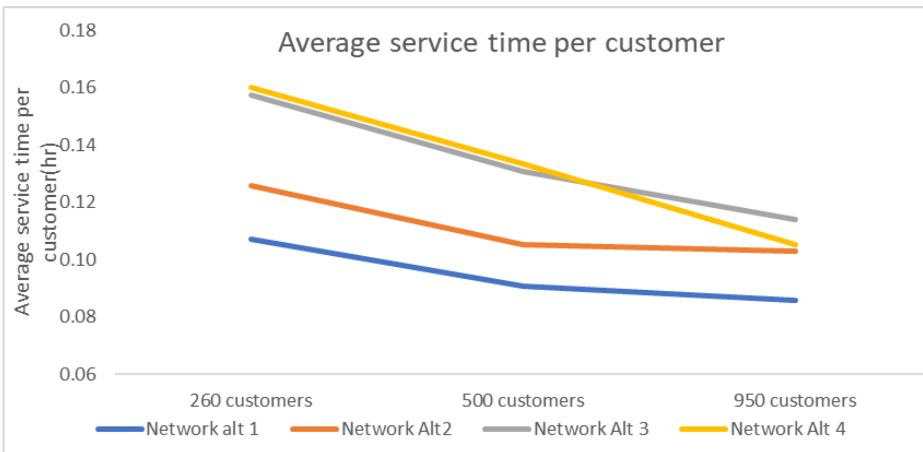


Figure 7: Average service time per customer

V. CONCLUSION AND FUTURE WORK

This research proposes a DST for LSPs to strategically evaluate the performance of urban transshipment networks with LEFVs for serving their customers within a LEZ. The DST is proposed mainly due to two reasons. Firstly, ex-ante performance evaluation of new logistics networks is crucial as their adoption involves a significant commitment of LSP's resources over a more extended period. Second, executing the process before any form of application (trials /pilots) is complex as the data required for performance measurement is not readily available. A scenario-based framework is employed for the DST as it helps logistics practitioners analyze the performance of networks for multiple what-if situations. All the network alternatives in the DST are assumed to have a generalized structure. The application of the DST on the synthetic case study has demonstrated the capability of this model to assist LSPs in evaluating the performance of the urban transshipment network. The proposed model can simulate closely the network configuration, which will be adopted by an LSP and to derive the quantitively the data adequate for its strategic performance evaluation. The model also is capable of solving large realistic problems without the need for sophisticated solving approaches. However, opportunities to improve the proposed model and extending the DST are identified for future work.

- <u>Improvements to the iterative solution algorithm</u>: As explained in section 3.2, the solver algorithm proposed for solving the approximate 2e-LRP model was missing a dynamic improvement link between the clustering model and the LRP. This missing link caused the peaks in minimum TLC vs. the number of clusters n_c plots. Therefore, the development of a new heuristic solution procedure integrated with this improvement link can result in a solution closer to the optimum global point.

- Sophisticated approximation and optimization models: Extension to the CA model by Figliozzi (2008) was developed by Winkenbach et al. (2016), called as augmented routing cost estimation formula (ARCE). This approximation formula accounts for different vehicle capacities, service times, and combined pickup and delivery routes. Thus, integrating this approximation method could estimate, precisely, the distances travelled by the LEFVs in last-mile delivery services. Furthermore, the integer linear LRP model can be extended to allow multiple product flow; heterogenous vehicles fleet both at the depot as well at micro hubs, customer delivery routes starting from micro hubs as well as the depot.

- Creative network alternatives: In the present research, only a single echelon or two-echelon distribution networks are considered. However, as turnover is a critical component of the economic performance of such networks, a third echelon can possibly be added to the last-mile delivery network to bundle their deliveries together in a UCC. Evaluating the performance of such innovative schemes would require extending the approximated 2E-LRP model to cope with multiple echelons.

- Extending the use of decision framework: Although the DST is intended for the application of private logistics firms, the proposed DST model be applied by local authorities to evaluate the impact of their LEZ polices on LSPs engaged in last-mile distribution services. The area of LEZ and LEZ entry penalties can be varied across demand scenarios to predict the resulting network adaptations by a typical LSP. Furthermore, The DST can be integrated into an agent-based simulation to check how LSPs having different customer densities will behave if LEZ is introduced into their service regions.

References

Amodeo, L., Lamari, D., Musolino, G., Placido, V., Polimeni, A., Praticò, M., & Vitetta, A. (2015). An ex-ante evaluation of last-mile freight distribution services for city logistics. In *Urban Transport XXI* (Vol. 1, pp. 291–302). WIT Press. https://doi.org/10.2495/ut150231

Ansari, S., Başdere, M., Li, X., Ouyang, Y., & Smilowitz, K. (2018, January 1). Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. *Transportation Research Part B: Methodological*. Elsevier Ltd. https://doi.org/10.1016/j.trb.2017.09.019

Aykin, T. (1995). The hub location and routing problem. *European Journal of Operational Research*, *83*(1), 200–219. https://doi.org/10.1016/0377-2217(93)E0173-U

Baldacci, R., Hadjiconstantinou, E., & Mingozzi, A. (2004). An exact algorithm for the capacitated vehicle routing problem based on a two-commodity network flow formulation. *Operations Research*, *52*(5), 723–738. https://doi.org/10.1287/opre.1040.0111

Boccia, M., Crainic, T. G., Sforza, A., & Sterle, C. (2010). A metaheuristic for a two echelon location-routing problem. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 6049 LNCS, pp. 288–301). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-13193-6_25

Clarke, S., & Leonardi, J. (n.d.). *Consolidating deliveries of retail and non-retail clients into single electric van deliveries*. Retrieved from www.london.gov.uk

Contardo, C., Cordeau, J. F., & Gendron, B. (2013). A computational comparison of flow formulations for the capacitated location-routing problem. *Discrete Optimization*, *10*(4), 263–295. https://doi.org/10.1016/j.disopt.2013.07.005

Contardo, C., Hemmelmayr, V., & Crainic, T. G. (2012). Lower and upper bounds for the two-echelon capacitated location-routing problem. *Computers and Operations Research*, *39*(12), 3185–3199. https://doi.org/10.1016/j.cor.2012.04.003

Crainic, T.G., Sforza, A., & Sterle, C. (2011). Location-Routing Models for Two-Echelon Freight Distribution System Design Location-Routing Models for Two-Echelon Freight. *CIRRELT Working Paper*, 28. Retrieved from www.cirrelt.ca

Crainic, Teodor Gabriel, 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

Crainic, Teodor Gabriel, Sforza, A., & Sterle, C. (2011). *Location-Routing Models for Two-Echelon Freight Distribution System Design Bureaux de Montréal : Bureaux de Québec*. Retrieved from www.cirrelt.ca

Cuda, R., Guastaroba, G., & Speranza, M. G. (2015a). A survey on two-echelon routing problems. *Computers and Operations Research*. https://doi.org/10.1016/j.cor.2014.06.008

Cuda, R., Guastaroba, G., & Speranza, M. G. (2015b). A survey on two-echelon routing problems. *Computers and Operations Research*, *55*, 185–199. https://doi.org/10.1016/j.cor.2014.06.008

Dablanc, L., & Montenon, A. (2015). Impacts of environmental access restrictions on freight delivery activities example of low emissions zones in Europe. *Transportation Research Record*, *2478*, 12–18. https://doi.org/10.3141/2478-02

Drexl, M., & Schneider, M. (2015, March 1). A survey of variants and extensions of the location-routing problem. *European Journal of Operational Research*. Elsevier. https://doi.org/10.1016/j.ejor.2014.08.030

Figliozzi, M. A. (2008). Planning approximations to the average length of vehicle routing problems with varying customer demands and routing constraints.

Transportation Research Record, *2089*(2089), 1–8. https://doi.org/10.3141/2089-01

Gao, S., Wang, Y., Cheng, J., Inazumi, Y., & Tang, Z. (2016). Ant colony optimization with clustering for solving the dynamic location routing problem. *Applied Mathematics and Computation*, *285*, 149–173. https://doi.org/10.1016/j.amc.2016.03.035

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. In *International Journal of Production Economics* (Vol. 87, pp. 333–347). Elsevier. https://doi.org/10.1016/j.ijpe.2003.08.003

Huber, S., Klauenberg, J., & Thaller, C. (2015). Consideration of transport logistics hubs in freight transport demand models. *European Transport Research Review*, *7*(4), 1–14. https://doi.org/10.1007/s12544-015-0181-5

Lee, J., Kim, C., & Wiginton, L. (2019). *Delivering Last-Mile Solutions: A feasibility analysis of microhubs and cyclelogistics in the GTHA*. Retrieved from https://www.pembina.org/reports/delivering-last-mile-solutions-june-2019.pdf

Merchan, D., Blanco, E. E., & Winkenbach, M. (2016). Transshipment networks for last-mile delivery in congested urban areas. In *ILS 2016 - 6th International Conference on Information Systems, Logistics and Supply Chain*.

Prodhon, C., & Prins, C. (2014, October 1). A survey of recent research on location-routing problems. *European Journal of Operational Research*. Elsevier. https://doi.org/10.1016/j.ejor.2014.01.005

Quak, H., Nesterova, N., & Van Rooijen, T. (2016). Possibilities and Barriers for Using Electric-powered Vehicles in City Logistics Practice. In *Transportation Research Procedia*. https://doi.org/10.1016/j.trpro.2016.02.055

Rybakov, D. S. (2017). Total cost optimisation model for logistics systems of trading companies. *International Journal of Logistics Systems and Management*, *27*(3), 318. https://doi.org/10.1504/ijlsm.2017.084469

Tragantalerngsak, S., Holt, J., & Rönnqvist, M. (2000). Exact method for the two-echelon, single-source, capacitated facility location problem. *European Journal of Operational Research*, *123*(3), 473–489. https://doi.org/10.1016/S0377-2217(99)00105-8

Uchoa, E., Pecin, D., Pessoa, A., Poggi, M., Vidal, T., & Subramanian, A. (2017). New benchmark instances for the Capacitated Vehicle Routing Problem. *European Journal of Operational Research*, *257*(3), 845–858. https://doi.org/10.1016/j.ejor.2016.08.012

Winkenbach, M., Kleindorfer, P. R., & Spinler, S. (2016). Enabling urban logistics services at la poste through multi-echelon location-routing. *Transportation Science*, *50*(2), 520–540. https://doi.org/10.1287/trsc.2015.0624