ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

INTEGRATED MANAGEMENT OF MIXED FLEETS OF ELECTRIC AND CONVENTIONAL VEHICLES UNDER ROUTING CONSIDERATIONS

Ph.D. THESIS

Reema Talab Hammad AL-DALAIN

Department of Management Engineering

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

ROTALAMA ETMENLERİ ALTINDA ELEKTRİKLİ VE KONVANSİYONEL ARAÇLARIN KARMA FİLOLARININ BÜTÜNLEŞİK YÖNETİMİ

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KASIM 2021

Reema Talab Hammad AL-DAL'AIN, a Ph.D. student of İTU Graduate School of Science Engineering and Technology, student ID 507162014 successfully defended the thesis/dissertation entitled "INTEGRATED MANAGEMENT OF MIXED FLEETS OF ELECTRIC AND CONVENTIONAL VEHICLES UNDER ROUTING CONSIDERATIONS", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my family

FOREWORD

This journey would not have been as amazing without the fascinating people I met along the road. I would first and foremost like to offer my deepest gratitude to my supervisor Professor Dilay ÇELEBİ GONIDIS for the opportunity to carry out this research project and for her tremendous encouragement, patience, motivation, and immense knowledge during my PhD.

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I am forever indebted to my parents, my brothers, and my grandparents for their unconditional love and support throughout my life.

October 2021

Reema AL-DALAIN
(Management engineering)

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ABBREVIATIONS

AC	: Alternative Current
BBA	: Branch and Bound Algorithm
CO_2	: Carbon Dioxide
CV	: Conventional Vehicles
CVRP	: Capacitated Vehicle Routing Problem
DC	: Direct Current
DCVRP	: Distance Capacity Vehicle Routing Problem
DVRP	: Distance Vehicle Routing Problem
EAFO	: European Alternative Fuels Observatory
ECVs	: Electric Commercial Vehicles
EPA	: Environmental Protection Agency
EV	: Electric Vehicles
EVI	: Electric Vehicles Initiative
GA	: Genetic Algorithm
GHG	: Greenhouse Gas
G-VRP	: Green Vehicle Routing Problem
HDT	: Heavy-Duty Truck
HFVRP	: Heterogeneous Fleet Vehicle Routing Problem
HVRP	: Heterogeneous Vehicle Routing Problem
ICCVs	: Internal Combustion Commercial Vehicles
IEA	: International Energy Agency
Kg	: Kilogram
KWh	: Kilowatt Hour
LCV	: Light Commercial Vehicle
LNG	: Liquefied Natural Gas
MBFM	: Mixed Bus Fleet Management
MDT	: Medium Commercial Vehicle
Mpg	: Miles per gallon
MVRP	: Multi-Depot Vehicle Routing Problem
MVRPTW	: Mixed Vehicle Routing Problem With Time Window
NLABC	: New Life Additional Benefit-Cost
PVRP	: Periodic Vehicle Routing Problem
SA	: Simulated Annealing
SDVRP	: Split Delivery Vehicle Routing Problem
SOC	: State of Charge
SVRP	: Stochastic Vehicle Routing Problem
TCO	: Total Cost of Ownership
TDVRP	: Time Dependent Vehicle Routing Problem
TSP	: Travelling Salesman Problem
UCC	: Urban Consolidation Centers
UK	: United Kingdom
VRP	: Vehicle Routing Problem
VRPB	: Vehicle Routing Problem With Backhaul

VRPTW **:** Vehicle Routing Problem With Time Window

SYMBOLS

$\boldsymbol{a_i, b_i}$	: The time window for each customer i.
$\boldsymbol{A_k}$	: Maximum age of vehicle.
$\boldsymbol{B_t}$	: Budget at the beginning of year t.
$\boldsymbol{C}$	: Annual working days.
$\boldsymbol{D_t}$	: Annual miles that needed to be travelled at year t.
$\boldsymbol{e_{fk}}$	: CO_2 emissions cost of age f type k vehicle per mile
ec	: CO_2 emissions penalty
er	: Electricity inflation rate
$\boldsymbol{F_{fk}}$	: Fuel tax cost of age f type k vehicle per mile.
FV	: Future value.
$\boldsymbol{d_{ij}}$	: The distance between customers i and customer j.
$\boldsymbol{dr}$	: Discount rate.
$\boldsymbol{G_k}$	: Vehicle capacity of type k.
g	: Gallon
$\boldsymbol{H_k}$	: The operational range of vehicles of type k.
$\boldsymbol{h_{fk}}$	: Initial number of age f , type k vehicle at time zero.
I	: set of customers vertices.
K	: Type of truck.
$\boldsymbol{L_{ij}}$	: The travel time between customers i and customer j
$\boldsymbol{M_{tk}}$	: Number of available vehicles of type k at time t.
n	: Lifetime of asset
$\boldsymbol{o_k}$	: Operational cost
$\boldsymbol{P_{tk}}$	: The number of new type-k vehicles purchased at time zero
PV	: Present value
$\boldsymbol{Q_{fk}}$	: Maintenance cost of age f type k vehicle per mile
$\boldsymbol{q_i}$	: Customer’s demand.
$\boldsymbol{R_{ftk}}$	: The number of age- f, type-k vehicles salvage at the end of year t,
r	: Annual depreciation rate.
$\boldsymbol{S_i}$	: Service time of each customer.
$\boldsymbol{s_{fk}}$	: The salvage value of an age f type-k vehicle
t	: Time period.
T	: Maximum time.
$\boldsymbol{U_{ik}}$	: The load of vehicle k after visiting customer i.
$\boldsymbol{u_{fk}}$	: Utilization of age f , type k vehicle.
$\boldsymbol{v_k}$	: The purchasing cost of a type k truck in dollars.
$\boldsymbol{W_{ftk}}$	: The number of age- f, type-k vehicles used in year t,
$\boldsymbol{X_{ijk}}$	: $X_{ijk} = 1$, if a vehicle type k traveling from i to j, OW $X_{ijk} = 0$
$\boldsymbol{Y_{ij}}$	: The vehicle load from the customer i to j.
$\boldsymbol{f}$	: Age of vehicles.
$\boldsymbol{fr}$	: Fuel inflation rate

$\boldsymbol{l}$	**:** Prime lending rate
$\boldsymbol{\rho}$	**:** Price index
$\boldsymbol{\tau_i}$	**:** The start time of each customer service.
μ	**:** Very large number.
%	**:** Percentage.
$	**:** USD Dollar

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INTEGRATED MANAGEMENT OF MIXED FLEETS OF ELECTRIC AND CONVENTIONAL VEHICLES UNDER ROUTING CONSIDERATIONS

SUMMARY

Planning and managing a set of freight delivery vehicles to minimize the total costs have always been a pressing issue in the transportation industry. However, recently and due to the environmental challenges, minimizing the greenhouse gas emissions in freight transport has become just as important as minimizing costs. In the race of dominance, the conventional vehicles used to overtake the electric vehicles in many aspects such as acquisition cost and refueling-recharging time, however effective management of electric vehicles in freight operations along with efficient cost planning throughout their lifecycle is expected to increase their adoption rate in urban freight. For heavy and medium duty vehicles there is uncertainty attached to the adoption rate due to limited driving range and charging battery, where companies might face losses of profit if vehicles needed to stop many times and for long periods during the day. Therefore, merging the electric vehicles with conventional vehicles in urban freight fleets can help to overcome the additional constraints induced by the specific characteristics of electric vehicles. A common practice for fleet mixed decisions is to use techniques that have been developed for managing conventional vehicles. These techniques may fall short in managing fleets with electric vehicles effectively.

In this thesis, an attempt has been made to present a new perspective to the problem of managing a mixed fleet of electric and conventional vehicles in urban freight by integrating two models; fleet size and mixed vehicle routing problem with time window and replacement model. Our study was motivated by the recent practice of involving alternative vehicles in existing fleets as a response to the recent global advocates of minimizing the greenhouse gas emissions generated from using conventional vehicles in the transportation sector.

We first consider a fleet size and mixed vehicle routing problem with time window to minimize the operational cost for different fleet compositions of electric and conventional vehicles, in which many constraints such as time window, limited distance range, and capacity are considered. Then we feed the results into a replacement model to find the best fleet mix policy. The replacement model is used to decide the optimal time periods to replace the used vehicles with a new one, taking into consideration different economic costs such as: annual discount rate, and energy prices for both fuel and electricity, along with the initial fleet compositions, and the planning time horizon.

The methodology is implemented on generated and real life problems. Results from the computational experiments show that efficient planning of electric vehicles in urban operations can increase their presence compared to conventional vehicles. This is an important insight, since it shows that the adoption rate of electric vehicles in urban freight fleets may increase with better planning techniques, related to electric

vehicles or with the increased experience of operational managers with electric vehicles.

ROTALAMA ETMENLERİ ALTINDA ELEKTRİKLİ VE KONVANSİYONEL ARAÇLARIN KARMA FİLOLARININ BÜTÜNLEŞİK YÖNETİMİ

ÖZET

Kentselleşme ile birlikte sera gazı salınımı ve enerji kaynaklarındaki azalma çok büyük problemler haline gelmiştir. Şehir nakliyeciliğinde elektrikli kullanımı, bu çok az miktarda karbondioksit salınımı, daha az gürültü, daha az kirlilik sağlamaları ve yenilenebilir enerji kaynakları ile çalışabilmelerinden dolayı bu problemlere bir çözüm olabilir. Elektrikli taşıtların bu avantajlarına ragmen, kısa sürüş menzili, yüksek fiyatları ve batarya maliyetlerindenn dolayı kentsel nakliyecliğinde kullanımı halen çok geride kalmıştır. Ayrıca bir çok ülkede şarj istasyonlarının olmaması elektrikli taşıtların bu alanda gelişmesi yönünde büyük engel teşkil etmektedir.

Konvansiyonel taşıtlar elektrikli taşıtlar göre bir çok yönde daha üstünken, son zamanlarda elektrikli taşıtların yüksek teknoloji ile gelişitirilmiş olması, piyasaya sunulması ve çevresel problemlerdeki sorunların azaltılması, elektrikli taşıtları daha rekabetçi bir konuma getirmiştir. Elektrikli taşıtların etkili bir şekilde yönetimi ve ürün ömrü için etkin maliyet planlamaları ile birlikte şehir içi nakliyede adaptasyonunu arttırması beklenmeketdir. Dünyadaki bir çok firma çevresel problemlerden dolayı konvansiyonel taşıtlarla birlikte elektriksel taşıtların etkili bir şekilde yönetimi ve ürün ömrü için etkin maliyet planlamaları ile birlikte şehir içi nakliyede adaptasyonunu arttırması beklenmeketdir. Dünyadaki bir çok firma çevresel problemlerden dolayı konvansiyonel taşıtlarla birlikte elektriksel taşıtları da kullanmaya başlamıştır. Konvansiyonel taşıtların elektirikli taşıtlarla bilirkte kullanımı elektriksel taşıtların kısa sürüş menzili ve şarj edilme gibi problemlerinin ortadan kaldırılma konusunda etkili olmuştur. Filo için kullanılan yaygın bir uygulama geleneksel taşıtların geliştirilmiş teknikleriyle birlikte kullanımı ile yönetmektir. Bu karma teknikler elektriksel taşıtların kullanılmaya başlaması ile azalmıştır.

Bu tez kapsamında, elektriksel taşıtların şehir içi nakliyede kullanılması alanında adaptasyon düzeyi, operasyonal planlamaların filo yatırımlarındaki etkisine bakılarak araştırılmış ve ayrıca güzergah birleştirilmesi, filo bileşimlerdeki düzenlemelerin elektrikli taşıtların şehir içi nakliyedeki üzerine etkisi incelenmiştir. Elektrikli karma filo modelleri ile ilgili daha önceki çalışmalar taşıtların yaşına bağlı olarak sabit nakliye maliyetlerini varsayar. Bu varsayım yenileme ilkesini belirlemeyi kolaylaştırmasına ragmen, gerçek yaşam durumları için belirsiz ve gerçekçi değildir çünkü rota kısıtlamaları operasyonel maliyette çok önemli bir yer tutmaktadır

Problemi daha net bir şekilde tanımlayabilmek için, şehir içi nakliyede elektrikli ve konvansiyonel taşıtlar için araç rotalama ve filo bileşim kararlarını birlikte ele alan yeni bir entegre metotla en iyi taşıt yenileme ilkesi belirlenmiştir. Bu modelde operasyonel maliyetler Zaman Pencereli Karma Araç Rotalama problemlerine (ZPKAR) göre hesaplanmıştır. Bu hesaplamada, taşıt yenileme modelindeki olası

tüm filo bileşimleri için zaman penceresi, mesafe kısıtı ve kasapasite gibi sınırlamalar göz önüne alınarak hesaplama yapılmıştır. Elde edilen sonuçlar yenileme modelinde giriş verisi olarak kullanılmıştır. Yenileme modeli, kullanılmış taşıtların değişimi için en uygun zamanı ekonomik maliyetler, yıllık amortisman oranı, elektrik ve yakıt harcamaları gibi faktörlere göre belirlemektedir. Bununla birlikte başlangıç filo bileşimleri, planlama süresi, bütçe, taşıt başına katedilen mil, yıllık taşıt sayısı gibi etmenler de göz önünde bulundurulmaktadır. Yenileme modelindeki taşıt özelliklerine ek olarak, taşıtın maksimum yaşı, edinim maliyeti, tamir onarım maliyetleri, bakım maliyetleri, karbondioksit gaz salınımı, vergiler ve taşıt cinsi gibi parametreler de yer almaktadır. Tüm bu kriterler yenileme modelinde en önemli unsuru tahmin etmemizi sağlamaktadır. Bu unsur ise, tüm taşıtlar için ZPKAR tarafından belirlenen rotalar sonucu ortaya çıkan yıllık katedilen mesafedir.

Geliştirdiğimiz model elektrikli ve konvansiyonel taşıtların karma filo performansları için yapılan klasik değerlendirmenin ötesinde bir analiz olanağı sunmaktadır. Bu sayede farklı karma filo bileşimlerinin, operasyonel aralıkların ve maliyetlerin filo karma ilkesine etkisi analiz edilebilmektedir. Önerilen yöntem gerçek veya kuramsal hayat problemlerine uygulanabilmektedir. Hesaplamalı deney sonuçlarımıza göre, etkili bir rota planlama ile elektrikli taşıtların şehiriçi yük taşımacılığında kullanımı konvansiyel taşıtlara kıyasla artmaktadır. Bu çok önemli bir sonuçtur, çünkü etkili bir planlama ile elektrikli taşıtların şehiriçi yük taşımacılığına adaptasyonun mevcut duruma göre artırılabileceğini göstermektedir.

Önerilen yöntem herhangi bir karma filo planlama problem için doğrudan kullanılabilecektir. Fakat yöntemin çok karmaşık hesaplamalı bir yapıya sahip olmasından dolayı, problemin boyutu müşteri sayısı yönünden arttıkça, tam bir çözüm sunması çok zordur. Ayrıca araç rotalama modeli, aracın şarj için depoya dönmesi durumunda bazı modifikasyonlar gerektirecektir. Elektrikli taşıtların adaptasyon oranına etkisini görebilmek için sonuçların genellenmesi gereklidir ve bu konuda başka çalışmalar gerekmektedşr. Bunun için taşıt özellikleri ve sera gazı salınım maliyetleri de göz önünde bulundurulmalıdır. Ayrıca elektrikli taşıt endüstrisinde önemli teknolojik ilerlemeden dolayı ve yakıtlardaki sabit değişime göre, şu anki mevcut sonuçlar gelecekte güncellenecektir.

Duyarlılık analizi sonuçlarına göre, filo bileşiminde daha çok elektrikli taşıt kullanabilmesi için, bataryaların ömür süresi artırılmalıdır, bu da çeşitli optimizasyon teknikleri ile sağlanabilir. Bununla birlikte bataryaların ömür süresi ile ilgili bir çok belirsizlik halen mevcuttur. Gelecekteki çalışmalar için, model şarj olanakları eklenerek genişletilebilir, çünkü elektrkli taşıtlar rota esnasında tamamen veya kısmi olarak şarj edilebilirler. Sonrasında farklı şarj stratejilerinin batarya ömür süreleri üzerindeki etkisi analiz edilebilir ve bundan dolayı elektrkli taşıtlar daha rekabetçi hale getirilebilir. Karbondioksit gaz salınım maliyetleri ve batarya değişim seçenekleri ile gözlemlerimize göre geliştirdiğimiz entegre model temel filo yönetim modeline kıyasla elektrikli taşıtların adaptasyon oranın arttığını söylemektedir. Ayrıca önerdiğimiz model konvansiyonel ve elektrikli taşıt maliyetlerinin birbirine çok yakın olduğu durumlarda daha etkili olacaktır. Bununla birlikte güvenilir sonuçlar için gelecekte daha çok örneklem üzerine çalışılmalıdır.

Şehir nakliyeciliği kapsamlı bir konu olup bir çok faktör, dikkate alınacak hususlar ve problemler içerir. Son zamanlarda, elektrikli taşıtların kullanımı yoğun ilgli görmüştür, yalnız bu taşıtların şehir nakliyeciliğinde kullanımı için adaptasyonun arttırılması ile ilgili daha çok araştırmaya ihtiyaç vardır. Gelecek çalışmalarda şarj konusunu da kapsayan modellerim önemi artacaktır.

Modelleme yönünden ise, stokastik seyahat süresi ve hizmet süresi gibi dinamik parametreler de ele alınabilir. Bu sayede dinamik filo boyutu ve karma araç rota problemleri gelecekte çalışılabilir.

1. INTRODUCTION

This introductory chapter presents the background, the scope, and the purpose of this thesis. In addition, the importance of the main topic “the impact of effective management on the adoption rate of electric vehicles in a fleet composed of electric and conventional vehicles in urban freight” is illustrated. The main contributions of this thesis are also mentioned, followed by the outline of this thesis and the key terms.

1.1 Background

The greenhouse gas emissions have a direct contribution in climate changes and global warming problems. It has been reported that approximately 24% of direct CO_2 emissions in 2019 were caused by the transportation sector IEA (2019), and the percentage is expected to increase due to the fast growth of population along with the new online shopping behaviors, and home delivery. This drives many researchers to characterize the current logistic system as unsustainable from three different perspectives; economical, environmental, and social (Montreuil et al, 2012). To address this issue, efforts have been made to encourage the transportation industry to adopt decarbonization strategies to cope with the growth of the environmental challenges. Increasing energy efficiency, reducing the intensity of emissions, and switching from fuel to electricity are among the major decarbonization opportunities in urban areas (Quigley, 2019). Therefore, presenting genuine alternatives for the use of conventional vehicles within urban areas can help to move toward sustainability.

Electric vehicles (EVs) are a good candidate to reduce the greenhouse gas (GHG) emissions in the transportation sector, since they have the ability to be charged by renewable energy; therefore, they produce almost zero emissions. Over the last decades, a lot of effort has been put into increasing the adoption rate of EVs in urban freight distribution as a response to the environmental challenges. However, it remains limited and mostly deployed as light commercial vehicles ((Bunsen et al 2019), where in Europe the light truck registration in 2020 exceeded 37000 units, while in China it was more than 3400 units. For the rest of the world the registration of light electric trucks was around 19000 units (IEA, 2021).

Besides being eco-friendly, electric vehicles can improve the efficiency of the transportation sector, as the cost per mile for electric vehicles is significantly lower than that of conventional vehicles. In addition, electric vehicles have fewer moving components compared to conventional vehicles, meaning that the maintenance and service will most likely be lower, beside the fast rate of growth and market penetration (Rahimi and Davoudi, 2018), also they can produce less noise (Teoh et al, 2018). Despite all those advantages, the adoption rate of electric vehicles in urban freight distribution faces many challenges such as limited driving range, high purchase and battery costs (Taefi et al, 2016), beside the absence of charging infrastructure (Ajanovic and Haas, 2016), and time required to recharge (Amirhosseini and Hosseini, 2018), along with technical and market challenges related to user's acceptance, safety regarding battery technology, and performance issues (Wu et al, 2017).

Charging stations continue to have a major impact on the presence of electric vehicles in urban freight. European cities invest highly in public charging of electric vehicles. Oslo, Paris, London, and Amsterdam reached about 4,300, 4,700, 5,800, and 9,100 charge points, respectively in 2019 (Hall and Lutsey, 2020). South Korea's government has planned to deploy 10,000 fast chargers by 2022 (Research and Market, 2020). Similarly, India has targeted to install 2,700 charging stations by 2023 inside cities with more than 4 million residents (Research and Market, 2020). As a result, the electrification of medium and heavy-duty trucks increasingly gained attention as they were promoted to be the ideal solution to decrease the greenhouse gas emissions in urban freight distribution. Different governments have presented ambitious policies to increase the adoption of electric vehicles in different sectors including the development of new charging methods and infrastructure. China's government is among the governments that has made active progress in developing government policies and regulation in subsidies for both electric vehicles and charging stations to increase the market share of electric vehicles (Song et al, 2020).

The urban freight transport system mainly concerns business-to-business delivery between different warehouses, shops, retailers etc. Due to the increase in the population and online shopping behaviors, the business-to-consumer deliveries have also increased. This results in a growing number of small deliveries, which are usually made by vans and cargo motorcycles. This is the costly, most polluting, and inefficient part of the transportation system. Electric vehicles may potentially replace these deliveries, as they are more suitable in short-distance transport for small freight volumes inside cities, which may reduce the environmental challenges related to the use of conventional vehicles. Mirhedayatian and Yan (2018) investigate the policies supporting EVs in urban freight transport by establishing a theoretical framework combining an optimization model with economic analysis to evaluate individual company’s actions in response to policies for electric vehicles. According to the authors, there are three main policies: purchase subsidies, low-emission or congestion zones, and vehicle tax exemptions. Quak et al. (2016) evaluate the feasibility of using electric powered vehicles in city logistics practices from a carrier's perspective. The authors argue that technological performance are among the most important factors, along with the limited production and availability of electric vehicles, more specifically the heavy duty electric freight vehicles. Moreover, the development of the technology is necessary for further optimization of EFVs integration into daily practices of transport operators.

Figure 1.1 shows the number of electric trucks sold from different types of trucks in 2018. As the figure shows, the heavy-duty trucks have a small share of the market, unlike the light- and medium-duty trucks, which make up 98% of the global battery electric trucks, where more than 160,000 units sold from light duty trucks in 2018. (Scriven, 2019).

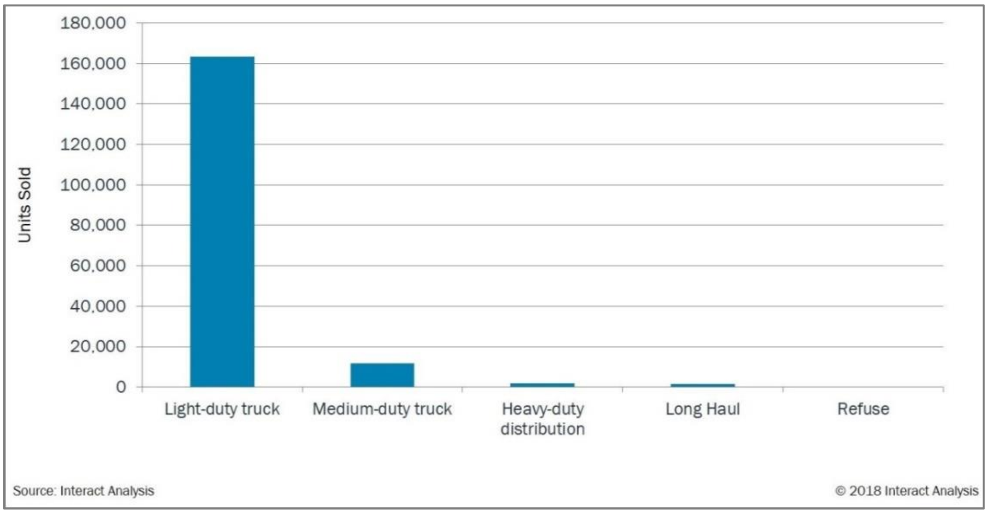


Figure 1.1: The number of units of electric trucks sold from each type (Scriven, 2019).

For more details, Figure 1.2 shows the electric truck registration for the biggest market; China, Europe, and the United States from 2015 to 2020. As the figure indicates, China dominates the category, with more than six thousand new registrations in 2020. In Europe, the electric truck registrations increase to reach 23%, which is around 450 vehicles, while in the United States increased to 240 vehicles (IEA, 2021).

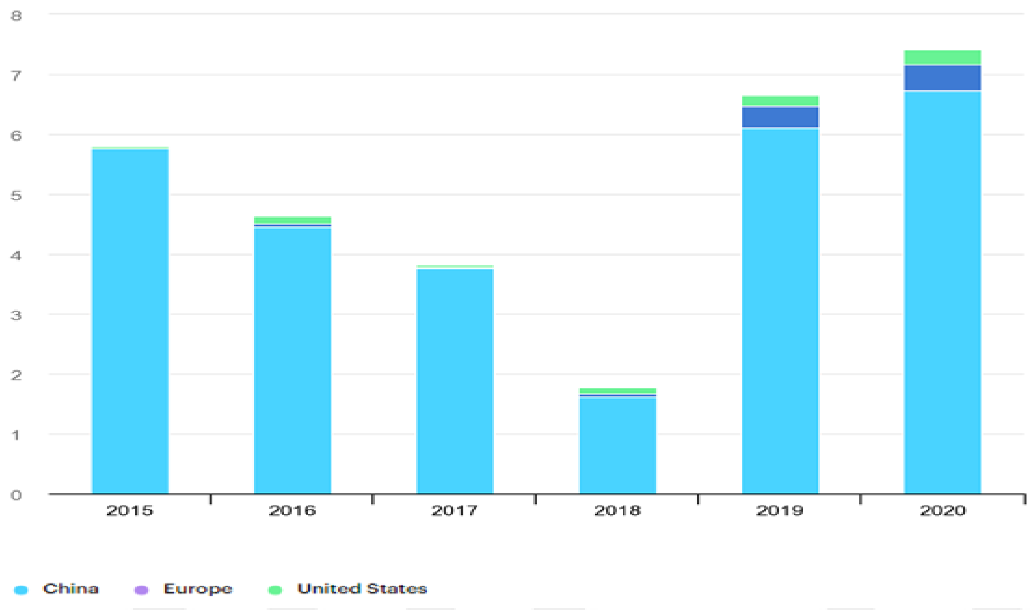


Figure 1.2: Electric truck registrations by region, 2015-2020 (IEA, 2021).

Different companies start producing electric vehicles that vary between light, medium, and heavy duty, such as delivery and pickup trucks, garbage trucks, buses, electric cargo motorcycles and many more. In 2020 there were around 30 medium-duty electrified models and 21 heavy-duty models offered in the market for sale worldwide (Lilley, 2020). Those numbers are expected to increase in the upcoming years, as the Electric Vehicles Initiative (EVI) set a goal to reach 30% market share for EVs by 2030 (including cars, buses and trucks) in order to meet the Paris Agreement targets (IEA,2020).

Several companies announce the production of electric heavy-duty trucks including: big rigs, semi-trucks, and delivery vans. For instance, BYD is a Chinese manufacturing company that is considered as the world’s largest company that produces electric vehicles in terms of number of e-trucks sold. Another company that takes the lead in the electric truck industry is Rivian, which is an American electric vehicle automaker company. The company gains its fame when amazon announced purchasing 100,000 electric trucks from the manufacture in order to achieve their goal to be net zero carbon by 2040 (Downing, 2020). Tesla also has an ambitious plan to present two heavy-duty electric models: one with a 300-mile range and one with a 500-mile range, with expected price range ($150,000 to $180,000) by the end of 2021 (Socio, 2021).

In order to achieve a tipping point in truck electrification, a near parity must be achieved with conventional vehicles, regarding the driving range, initial cost and charging infrastructure. Table 1.1 illustrated some of the barriers of using electric vehicles in urban freight. The barriers are grouped into three main categories: knowledge, technical, and economic barriers. Electric trucks are relatively new compared to conventional trucks; therefore consumers may have some concerns about their performance, reliability, and the technology advancement. Also there is a shortage regarding mentioning and clarifying the positive impact of electric vehicles on the environment.

Providing potential consumers with detailed information about electric vehicles and their benefits may increase their presence and adoption rate in urban freight. Another important issue is the storage capacity of the electric vehicles batteries, which determines their traveled distance. Range anxiety is considered one of the major problems facing the potential users of electric vehicles. Therefore, battery technology and safety are among the most significant technical barriers.

Table 1.1: The barriers of using electric trucks in urban freight.

Type of barriers	Barriers	Literature
Knowledge barriers	• Lack of verification and evidence on the performance of using e-trucks in urban freight. • Lack of knowledge on the latest technologies used in e-trucks. • Lack of awareness of the impact of using e-trucks on the environment.	(Adhikari et al, 2020)
Technical barriers	• Limited driving range. • User's acceptance. • Safety regarding battery technology	(Wu et al, 2017)
Economic barriers	• High acquisition cost • High battery costs	(Amirhosseini and Hosseini, 2018)

The total cost of ownership (TCO) e-Truck for many models will be close to the total cost of ownership for ICE trucks if the battery technology, vehicle performance, and safety of electric vehicles improve. McKinsey estimates that the adoption rate of e-Truck will exceed 30% by 2030 for different vehicle classes: light commercial vehicle (LCV), medium-duty truck (MDT), and heavy-duty truck (HDT) (Furnari et al, 2020). It is expected that the growth of the adoption rate will be faster for light commercial vehicles due to many reasons; first the high similarities with passenger electric vehicles regarding the battery and used technology. Second, the light duty trucks are used in last mile deliveries, where the distances in these routes are typically short, which means that the limited range of electric trucks will not be a barrier, and the battery will not need recharge during the routes. Unlike medium and heavy trucks which are mainly responsible for delivering goods between different warehouses and large distribution centers, where the daily routes are usually long and therefore the battery needs to be charged many times during the visits.

1.2 Scope of the Problem

Truck manufacturers racing to bring electric vehicles into the urban freight market motivated by the world's keen interest in reducing the greenhouse gas emissions, government incentives, and drop in acquisition and battery costs. In the scope of this thesis, the adoption rate of electric vehicles in urban freight is investigated by studying the impact of operational planning on fleet investment decisions, and the effect of combining routing and fleet composition in increasing the adoption rate of electric vehicles in urban freight distribution.

The adoption of electric vehicles in urban freight transport definition is inspired by the following definitions *"The sequence of stages through which a consumer progresses from first awareness of an innovation to final acceptance."* (Mahajan and Yoram, 1985) and "*The adoption process framework has been utilized to evaluate the potential viability of a new product"* (Blattberg and Golanty, 1978; Pringle et al., 1982; Silk and Urban, 1978). Therefore, we can define the adoption of electric vehicles in urban freight by: Moving the electric vehicles from the niche market to the mass market by illustrating their viability and economic feasibility in urban freight.

1.3 The Purpose of the Thesis

This research is motivated by the rapid electrification of the transportation sector as the recent promising technologies used in EVs offer an economical and technically feasible option to increase the sustainability in the transportation and logistics industry. However, some EV's characteristics impose a negative impact on the adoption rate of the electric vehicles in urban freight operation such as limited driving range and long charging time.

Therefore, the overall purpose of this thesis is:

Studying the impact of effective management of a mixed fleet composed of electric and conventional vehicles on the purchase decisions over a planning time horizon.

Fundamentally, the life cycle analysis and mixed vehicle routing model has been investigated in many researches for decades, although the analysis of alternative fuel vehicles performance specially electric vehicles still remain unfulfilled. Most importantly, none of the existing models integrated the fleet size and mixed vehicle routing model to calculate the operation costs for different fleet compositions.

The main objectives of this thesis are listed below:

- Understand environmental and economic factors that affect the adoption rate of electric vehicles in urban freight, in order to produce results that are directly relevant to real life situations.
- Propose a novel integrated model that considers both routing and fleet composition decisions by integrating fleet size mixed vehicle routing problem with time window and replacement model.

1.4 The Contributions

The key contributions of this work are highlighted as follows:

1. The research presents a new perspective to the research arena by introducing an integrated model that considers both routing and fleet composition decisions for using electric vehicles in urban freight distribution.

2. The thesis presents a formulation to find the best fleet mix policy based on integration process and the understanding of the operational characteristics of a fleet composed of electric and conventional vehicles.
3. Our contribution also includes a scenario analysis rather than the traditional method of evaluating the performance of a mixed fleet of electric and conventional vehicles, which allows us to address the impact of different fleet compositions, operation ranges and costs on the fleet mix policy.
4. The inconsistency factors that affect the adoption rate of electric vehicles are considered and a sensitivity analysis to study these factors is presented.
5. The presented research addresses most of real life vehicle's characteristics and economic factors that can be applied at any vehicle type and at any country.
6. A case study from a real life situation from the city of Istanbul-Turkey is presented to evaluate the performance of the proposed methodology.

1.5 Research Significance

In this section, we present the importance of the presented thesis from the literature point of view, where the main reasons are listed below:

1. The evaluation of using electric vehicles in fleet planning in urban freight has become more complex due to their fast technological advancement; therefore life cycle cost analysis over the age of vehicles is required. However such approaches are few in the literature (Davis and Figliozzi, 2013).
2. The incorporation of electric vehicles in the distribution freight activities especially in heterogeneous fleets shows a promising trend, with the rising importance of using sustainable strategies in road logistics and transportation. (de Armas et al, 2016)
3. The challenge of establishing a systematic and standard methodology for integrating the economic, environmental and social impact assessments is still lagging behind (Gundes, 2016).

1.6 Thesis Structure

This thesis is divided into three main parts; conceptual, mathematical, and application as illustrated in Figure 1.3, this allows the reader to follow the detailed investigation of this thesis in a more logical way. A more detailed overview of each chapter is presented below:

Chapter 1- Introduction: gives a general introduction to the problem that we proposed in this dissertation. And illustrate the scope of the problem, the motivation, and the main contributions.

Chapter 2- The Use of Electric Vehicles in Urban Freight: begins with defining the fleet management in urban freight, and illustrating the principle of sustainable urban freight transport system. This follows with various experiments that have adopted the use of electric vehicles in their operating fleets are also represented. Since this thesis presented a novel methodology, the literature is reviewed for both mixed vehicle routing problem and replacement models highlighting different aspects of logistics and urban freight.

Chapter 3- Methodology and Mathematical Model: discusses the approach we used to investigate presence of electric vehicles in a fleet composed of electric and conventional vehicles in urban freight over a planning time horizon. In addition, this chapter presents the two models used to calculate the optimal replacement policy for a mixed fleet. The first model is the mixed vehicle routing model with a time window, which is used to calculate the operational costs for different fleet compositions, while the second model is the replacement model. The purpose of the replacement model is to obtain the best replacement policy for a set of mixed fleet taking into consideration many economic and vehicular characteristics.

Chapter 4 – Computational Experiments: In this chapter, we presented the economic calculation of various parameters that is used in the models. Also computational experiments for the proposed methodology are obtained.

Chapter 5- Case Study: We choose to conduct a case study from a retail company in the city of Istanbul-Turkey. Conducting a case study in this thesis aims to investigate the performance of the presented methodology on a real life situation.

Chapter 6- Conclusion and Future Work: illustrate the key points of our finding in the presented thesis with a general summary of the contributions. In addition, the outlines of future research are also presented in this chapter.

1.7 Key Terms

- Fleet management: administrative approach companies follow to organize vehicles in a way that enhance the efficiency, reduce costs, and provide compliance with government regulations (Rouse, 2017).
- Fleet size: determining the number of vehicles in the fleet that is able to satisfy a complete transportation order while avoiding high costs related to fleet underutilization (Żak et al, 2011).
- Fleet mix: determining the optimal mix of vehicles from different types. (Bojovic and Milenkovic, 2008).
- Fleet composition: determining the fleet size and mix (Etezadi and Beasley, 1983).
- CO_2 emissions: colorless, odorless and non-poisonous gas formed by combustion of carbon and in the respiration of living organisms and is considered a greenhouse gas (OECD,2013).
- Logistics: The process of strategically managing the movement and storage of materials, finished parts and inventory through the organization and its marketing channels in a way that maximized the future profitability through the cost-effective fulfillment of orders (Behrenbeck et al, 2007).

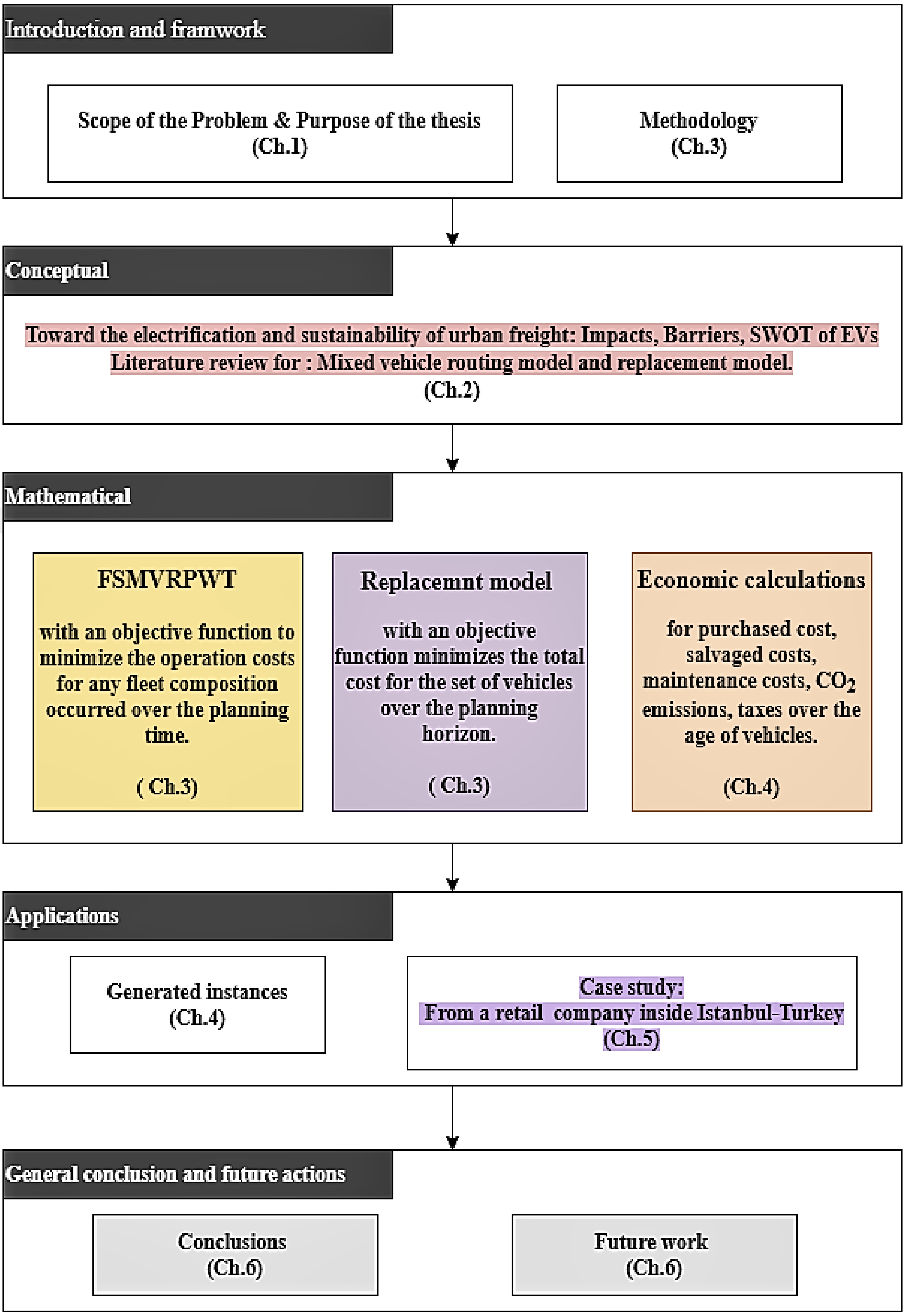


Figure 1.3: Dissertation organization.

2. THE USE OF ELECTRIC VEHICLES IN URBAN FREIGHT

This chapter aims to investigate relevant studies and literature related to electric vehicles in urban freight transport context and will be discussed in four sections. The first section will present the definition of fleet management in urban freight, followed by a discussion of the sustainability in urban freight operations. A review of solution strategies and applications is also discussed. Furthermore, overviews of several extensions of well-known variants of vehicle routing problem are reviewed. Finally, a literature related to fleet size and mixed vehicle routing problem with time window and replacement model is introduced.

2.1 Fleet Management in Urban Freight

Fleet management can be defined as an administrative approach companies follow to organize vehicles in a way that enhance the efficiency, reduce costs, and provide compliance with government regulations (Rouse, 2017). Depending on the nature of the problem, different approaches and methods can be formulated to solve fleet management problems, such as linear programming, nonlinear programming, goal programming, mixed integer and dynamic programming models. Linear programming for fleet management was discussed early in the literature by (Dantzig and Ramser, 1959). The authors used a linear programming model to minimize the number of tankers in order to meet a fixed schedule. Williams and Fowler (1980) developed a model to deal with the environmental constraints of vehicle acquisition policy and time-dependent fleet loads, the requests of vehicles were generated from probability distributions specific to the demand time series. Mixed integer programming formulation for large scale fleet management under a variety of side constraints, due to marketing, operational, maintenance restrictions was presented by (Rushmeier and Kontogiorgis, 1997). Ziarati et al. (1999) present branch and cut to select the type and number of vehicles that minimize the fixed and operational costs.

Calvete et al. (2007) introduced a goal programming approach to solve medium-sized delivery problem for a heterogeneous fleet of vehicles and provide an optimal solution in a reasonable time. Mathew et al. (2010) formulated a non-linear optimization problem for maximizing the total weighted average remaining life of the fleet subjected to different constraints, such as budget, demand, and non-negativity. The authors presented two solution approaches to solve the problem, genetic algorithm (GA) and a branch and bound algorithm (BBA). Jin and Kite-Powell (2000) introduced a dynamic model that optimizes utilization and replacement decisions where the optimal acquisition and retirement strategies were included. For more on this literature, (Oakford et al. 1981, 1984).

According to different articles and researches, the fleet management depends on several criteria (Rogic et al, 2007); the fleet size is among the most significant one, along with the size of the operative zone (the covering area of the operations) which is divided into three main categories: local, regional, and national. The third criterion is the routes of the vehicles, and it could be fixed daily routes, or variable daily routes. Another criterion is the time tolerance in delivering goods. In additions, the demand of a customer is also considered as a significant factor in fleet management planning, since it has a direct influence on the fleet size and fleet mix, as the demand of customers can vary in size, location of customers (local, regional) and many other characteristics, as a result, different types and/or size of fleets may be needed to meet the customers demand.

Different terms used to define the movement of goods and services within, into, and through urban areas. According to(Lindholm, 2012), ‘urban freight transport’, ‘urban goods transport’ and ‘urban distribution’ are among the most common terms. Since this thesis addresses the planning of a mixed fleet of electric and conventional vehicles freight in urban areas, we choose to use the urban freight transport term as it includes all types of transports in urban areas. It is important to have a clear definition of the term urban freight transport to use through this thesis, therefore, we decide to go with the definition of Allen et al.(2000), as they provide an inclusive definition:

(1)” all types and sizes of goods vehicles and other motorized vehicles used for (core) goods collections and deliveries at premises in the urban area.”

(2) “all types of goods vehicle movements to and from urban premises including goods transfers between premises, ancillary goods deliveries to urban

premises, money collections and deliveries, waste collections and home deliveries made from urban premises to customers."

(3)" service vehicle trips and other vehicle trips for commercial purposes which are essential to the functioning of urban premises".

In recent decades, fleet management in urban freight has increasingly drawn attention as an important topic in the research arena. Ambrosini and Routhier (2004) presented a number of studies and surveys in the area of urban freight transport and good movements. The authors compared the methods and results from different countries in Europe and Asia. Delaître and Routhier (2010) introduced two models that focus on the location and size of delivery in urban areas in order to help decision making processes to develop optimal delivery scenarios by estimating the number of goods vehicles in order to estimate the inconvenience on the overall traffic of the city. Holguín-Veras et al. (2020) presented an extensive discussion of initiatives that could be used to enhance the efficiency of urban freight activity in public-sector including financial approaches; logistical management; and demand/land use management.

Several factors affect the development of urban freight transport, such as customer behaviors, rapid technological advancement and economic factors, and with the ongoing urbanization these factors become even more in the future and have a higher influence on the movement in urban freight. Recently, there has been a growing trend of replacing stores by e-commerce and home delivery, due to many economic factors and health concerns. From the first sight, it seems like e-commerce can potentially decrease the movements and transportations, since the customers do not need to come to the stores. However, in reality, customers may replace or examine their products many times before purchasing. Consequently, there will be a growth in freight activities inside cities. The problem with the freight activities, that it has a direct impact on several aspects of daily life such as increasing greenhouse gas emissions, congestion, and pollution. Therefore, there is a need to understand and target the development of the urban freight system in conjunction with our goals of reducing emissions and enhancing life in urban areas. One option is to move towards a sustainable system.

Urban freight transport activities are indispensable for the growth of economy and individual income in urban areas, since they have a positive impact on increasing the commercial activities and the development inside cities, in addition to the economic growth. However, they cause a variety of negative impacts especially on the environment since most of the vehicles in urban areas use non-renewable energy sources to power, therefore; they produce a large amount of greenhouse gas emissions, noise, pollution, in addition to the waste of resources as shown in Table 2.1. A variety of social impacts can be noted as a result of urban freight operations, including accidents, traffic congestion, besides the health concerns.

Table 2.1 : The impacts of urban freight transport.

Type of impacts	Impacts	Literature review
Economic impacts	• Increase the development inside cities. • Increase individual income. • Increase the commercial activities. • Economic growth.	• (Browne and Allen, 2011)
Environmental impacts	• Greenhouse gas emissions. • Noise. • Waste of resources such as (oil, materials tiers). • Pollution. • Use non-renewable resources.	• (Stefanelli et al, 2015) • AustriaTech,2014)
Social impacts	• Health concerns. • Accidents • Traffic congestion. • Regulations and policies. • Urban expansion.	• (Foltyński, 2014a) • (Behrends et al, 2008) • (Datz et al, 2009)

Those impacts lead to unfavorable outcomes such as: health and safety concerns, global warming, and high transport costs, which eventually, reduce the quality of life in urban areas. Those impacts vary depending on the size and the infrastructure of the urban areas (Foltyński, 2014b). It is worth mentioning that the availability of data regarding the impacts of urban freights is poor compared to passenger transport.

2.2 Sustainability in Urban Freight

Moving toward sustainable alternatives and solutions to diminish the negative impacts in urban freight is a priority in urban freight planning. According to

Behrends et al (2008) the sustainable urban freight must meet the following objectives:

- *Ensuring the accessibility offered by the transport system to all categories of inhabitants, commuters, visitors and businesses, in line with the objectives below.*
- *Reducing the negative impact of the transport system on the health, safety and security of the citizens, in particular the most vulnerable ones.*
- *Reducing air pollution and noise emissions, greenhouse gas emissions and energy consumption (including contributing to meeting legislative requirements on air quality and environmental noise*
- *Improving the efficiency and cost-effectiveness of the transportation of persons and goods, taking into account the external costs. .*
- *Contributing to the enhancement of the attractiveness and quality of the urban environment.*

Figure 2.1 shows the principle of sustainable urban freight transport system based on the sustainable development principles (Behrends et al, 2008). It includes all parts that a sustainable system requires.

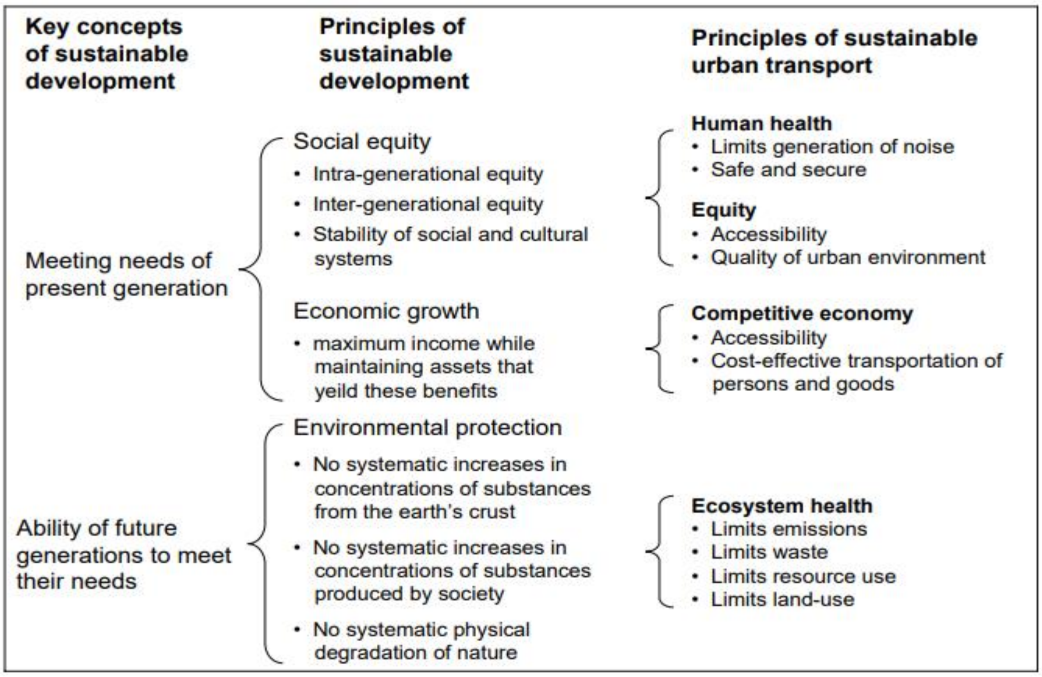


Figure 2.1: The principle of sustainable urban freight transport system (Behrends et al, 2008).

In general, we can consider a freight transport system to be a sustainable one, if it has a contribution to economic growth, environment, and social equity. Moving toward sustainable urban freight, whether by enhancing the current system or by introducing new technologies, faces many challenges such as lack in regulation and policies. Russo and Comi (2012) investigated the sustainability of urban freight in several European cities. The authors argue that the most important aspects to make urban mobility more sustainable is to promote a sustainable development strategy, monitoring and controlling the different types of costs generated by freight mobility in the urban area. The results also show that high cost investments are not required to obtain good results in terms of environmental goals. According to (Eleonor and Blinge, 2014) having awareness about freight transport is an important factor in increasing the sustainability in urban freight transport and can help in the policy making process. The authors also raise an important issue related to sustainability; that there is lack of motivation and knowledge for the local authorities to deal with the problem and rarely there is anyone responsible for freight transportation, which results in postponing the sustainable inside cities.

2.2.1 Urban freight transport strategies

Managing fleet for urban freight operations needs planning on tactical and operational levels as it faces continuous changes related to the increase in demand and just in time delivery, which require creative solutions and techniques from a theoretical and mathematical view. Researchers have introduced a number of strategies and practices to optimizing the urban freight operations, some of them are discussed below.

- **Road pricing**

The road pricing is the process of charging drivers for using the main roads. Despite being an easy strategy to execute, road pricing continues to be implemented at a low rate in many countries around the world. The main goal of this strategy is to decrease the traffic congestion and the environmental impact in urban areas. Road pricing targets all road participants, whether they are passengers or freight transport, but they affect the passenger's activities more than freight transport, since the companies tend to charge the customer with the extra cost resulting from the road pricing (Hans Quak, 2011). Ruesch (2004) presented an overview of road pricing in urban freight context. The authors implemented pricing schemes in European urban areas. They conclude that road pricing leads to more sustainable freight operations and has the ability to improve the efficiency of logistics. The authors also recommend that pricing should be linked with regulations, loading factors, and vehicle size and type.

- **Urban consolidation centers**

Allen et al. (2007) define the urban consolidation centers as "*A logistics facility situated in relatively close proximity to the geographic area that it serves (be that a city centre, an entire town or a specific site such as a shopping centre), to which many logistics companies deliver goods destined for the area, from which consolidated deliveries are carried out within that area, in which a range of other value-added logistics and retail services can be provided*."

The urban consolidation centers (UCC) considered as the most famous pooling solution to deal with city logistic in European cities (Chwesiuk and Kijewska, 2010; Van Duin and Muñuzuri, 2015), they are able to reduce the movement of vehicles inside cities, and therefore, reducing air pollution, noises and energy consumption. Faure et al. (2016) stated that the effectiveness of UCC is related to their locations and numbers.

- **Alternative fuel vehicles**

Efforts to shift the fuel vehicles to more eco-friendly vehicles in urban freight have been put. Experiments in different countries around the world using electric trucks, hybrid propulsion, and compressed- natural- gas trucks took place (Hans Quak, 2011). Different experiments show that using alternative vehicles has a positive impact on decreasing the pollution and noises and they are more energy efficient. Bethoux (2020) investigated the hydrogen fuel cell vehicles in road transport, the authors examined to what extent hydrogen fuel cell vehicles can satisfy the demands of the car industry and the possibility to implement the large scale FCV in road transport and their effect on the environment and the economy. It is worth mentioning that electric vehicles are among the most investigated vehicles to be used in urban freight operations to reach sustainability in urban freight operations.

- **Policies and regulations**

Setting policies to manage the freight delivery is one of the most important steps in urban freight sustainability, the main target of those policies is to limit the vehicles (trucks and freight delivery) access to the urban areas in a way that minimize congestion, pollution and improve air quality, such as setting delivery time windows, low emission zones, set a special time for deliveries, loading and unloading operations,and determining specific characteristics to the vehicles that are allowed to enter the urban areas (tonnage, size, age). One of the challenges facing the vehicle restriction strategy is the tendency for companies to start their business early in conjunction with rush hours, since most employees favor working within a fixed schedule, especially in the public sector, encouraging the employees to have a more flexible schedule with fixed hours could help more in establishing the vehicle restriction strategy widely. Table 2.2 shows some of the strategies that are implemented in some cities around the world.

Table 2.2 : Illustrates some of the strategies that have been applied in different cities.

Strategies	City	Literature
Roading price	London Stockholm Tokyo	(Russo and Comi, 2012) (Wappelhorst et al, 2020)
Consolidation centers	London Tenjin	(Browne et al, 2011) (Browne et al, 2005)
Alternative fuel vehicles	New York Australia London Amsterdam	(Browne et al, 2011) (Forde, 2020) (Baster et al, 2014)
Loading and unloading	Turin	(Diana et al, 2020)
Zero-Emission Zones	Rotterdam, Shenzhen	(Transport Decarbonization Alliance, 2020)

Among all strategies presented above, we choose focusing on using alternative vehicles, more specifically using electric vehicles in urban freight.

2.2.2 SWOT analysis of electric vehicles in urban freight

SWOT analysis is a strategic tool for evaluating the internal and external factors of an organization’s resources. The SWOT analysis stands for: Strength, Weakness, Opportunity, and Threats. Despite being simple, SWOT is a very efficient tool in assessing the current status of electric vehicles and estimating the future threats.

Table 2.3 illustrates the strength, weakness, opportunities, and threats of using EVs in urban freight distribution.

Table 2.3 : SWOT of electric vehicles in urban freight.

Strength	Weakness
• Low fuel costs (Rahimi and Davoudi, 2018),(Mouhrim et al, 2018)	• High purchase costs (Ahani et al, 2018) (Lebeau et al, 2013)
• Low maintenance costs (Feng and Figliozzi, 2013), (Kleindorfer et al, 2012), (Macharis et al, 2013)	• Limited driving range (Ahani et al, 2018) (Zhao and Lu, 2019)
• Eco- friendly (Foltyńsk, 2014b) (Stefanelli et al, 2015), (Aljohani and Thompson, 2018).	• Limited editions and models (Wu et al, 2017)
• Low noise (Teoh et al, 2018),(Ruesch, 2004), (Macrina et al, 2019)	• Charging infrastructure (Nallusamy et al, 2016), (Ashkrof et al, 2020)
	• Limited maintenance workshop (Adhikari et al, 2020).
Opportunities	**Threats**
• Increase in battery capacity (Redondo-iglesias et al, 2019)	• Lack in regulations and policies (Mirhedayatian and Yan, 2018), (Taefi et al, 2016), (Green et al, 2014)
• New vehicles have a higher driving range (Sanguesa et al, 2021), (Davis and Figliozzi, 2013)	• Unstable of energy prices (Adhikari et al, 2020)
• Technology development is better than ICVs (Ahani et al, 2018).	• Hydrogen vehicles (Manoharan et al, 2019), (Bethoux, 2020)
• Fast charging (Ajanovic and Haas, 2016), (Baster et al, 2014)	
• Environmental awareness (Adhikari et al, 2020)	

The main strength of using electric vehicles is the low running cost. According to EIA (2021) the gasoline prices equal \$3.02/gallon. Meanwhile, the prices of electricity equal \$0.0982/KWh. Secondly, (Feng and Figliozzi, 2013) reported that the maintenance costs for electric vehicles are 50% less than that of conventional vehicles. Also the positive impacts of using electric vehicles on the environment as they produce less noise and pollution. On the other hand the weakness related to its high initial cost, despite the government's incentives and subsidies. In addition, the limited driving range of electric vehicles due to the limited capacity of the battery is considered one of the main weaknesses of EVs along with the absence of charging infrastructure in many cities around the world. Also the scarce maintenance workshop, where the potential customer cannot make the purchase knowing that there is only a limited number of workshops that are able to fix the vehicles. Finally, the limited editions and models, even though the companies started offering different models and sizes, they still lack an extensive lineup of products compared to conventional vehicles. The opportunities lie in the new battery capacity, where the battery charge lasts longer, also the continuous technology improvements in electric vehicles, which results in a significant increase in the market demand of electric vehicles. The rapid advancement of electric vehicles charging technology should also be highlighted as an essential attribute in spreading the existence of electric vehicles. The first significant threat facing electric vehicles is the lack of regulation and policies. Secondly, the fluctuation in energy prices due to many economic factors. Finally, electric vehicles may face a prominent threat from the hydrogen vehicles, which are also considered as eco-friendly vehicles.

2.2.3 Studies and experiences

The idea of adopting green vehicles for urban freight distribution is not new. These vehicles are powered by green energy such as electricity. However, actual use and implementation of those alternative vehicles inside cities have started recently. In this section, we reviewed the initiatives implemented to reduce the environmental impacts of daily freight transport activities in the following companies:

- **Heineken**

The cities of Amsterdam/ Rotterdam have been supporting the use of electric vehicles in freight operations by using different incentives, such as government subsidies, and traffic regulation exemptions for logistics operators that use electric vehicles, for both vans and trucks. Heineken is a company that delivers their products to the shops and bars in cities throughout the Netherlands using 220 trucks, each covering between 100 and 250 km per day. They started adopting electric vehicles gradually in their operating fleet, currently they operate with 23 and 28 trucks from their Rotterdam and Amsterdam depots respectively. And they are targeting a 100% electric truck for secondary distribution centers in the near future, using renewable energy to recharge the vehicles.

Recently, Heineken, deploy six electric freight vehicles (with 12 tons) in Amsterdam and one electric truck (with 19 tons) in Rotterdam. Although they are currently using electric vehicles in their fleet, those are the first e-trucks as large as 12 and 19 tons to be operated in Heineken. Those trucks in Rotterdam and Amsterdam operate almost exclusively in the city centre. Their daily average cutting distance is 60 kms, with an average drop count of 13 to 17 deliveries.

- **IKEA**

Ikea is a Swedish company that designs and sells ready-to-assemble furniture, As of November 2020, there are 445 IKEA stores operating in 52 countries around the world. Ikea set a goal to become climate positive and clean transport in city center by cut CO_2 emissions in all stages of their value chain by 2030. They are taking significant steps on this front by using electric vehicles (EVs) or other zero-emission solutions. In New York City, Ikea is targeting to use 40 electric vehicles to service all five boroughs by May 2021. They are focusing now on building charging infrastructure at IKEA stores as it works toward their main target of having 100% zero emission deliveries by 2025 (Conshohocken, 2021). In addition, the Australian branch of IKEA has also committed to use all electric vehicles in their delivery fleet by 2025. The company now operates with a fleet of 100 trucks for large shipments and 250 trucks for small ones. They are using 7 electric trucks in delivering goods in Sydney, Perth and Melbourne.

- **DHL**

DHL is a company for package delivery, and express mail service ranging from domestic parcel delivery to international express. The company operates with nearly 100,000 vehicles all over the world. The company is aware of the amount of CO_2 emissions produced by those vehicles. Therefore, they decide to take further steps towards making the cities greener and reducing the impact of commercial vehicles on the environment. Recently, they started using, more eco-friendly way to distribute deliveries from the depots to their final recipients. In 2017, DHL set a plan, called Mission 2050, to reduce its net carbon emissions to zero by 2050 (Reid, 2019). The short term target for 2025 is to reduce emissions by operating clean services for 70% of the company's pickup and delivery services. Today, DHL uses more than 3,200 electric bikes, plus 9,000 other e-bikes and e-trikes all over the world, with potential increase in some markets. In London, DHL Express has launched ten new electric courier vans as part of UK fleet (DHL, 2021).

- **Amazon**

In support of the Paris agreement, Amazon had committed to be net zero carbon by 2040 by using electric vehicles and inventing new alternative delivery solutions. In 2019, Amazon ordered 100,000 electric delivery vehicles, which is considered as the biggest order ever for electric vehicles. Their plan is to operate with 10,000 new electric vehicles as early as 2022 and 100000 vehicles on the road by 2030 (Coren, 2019). Currently, Amazon operates using hundreds of electric vehicles around the world, and integrating charging infrastructure to use. In addition they are using e-cargo bikes for deliveries in some European cities and New York City.

- **Office delivery in London**

In 2009, London made the decision to trial a new urban delivery system to reduce the environmental impact of the freight operation inside the city (Browne et al, 2011). The trial involved the use of an urban micro-consolidation centre along with electric vans and electric cargo tricycles. The micro consolidation centre was located in the city of London, which is the historic core of London with an area of 2.9 km^2. The electric vans and tricycles deliver the parcels from the centre to the final customers, which were all located in London as well.

The results indicate that the use of a micro-consolidation centre along with a total fleet of electric vans and cargo tricycles reduced the total distance driven per parcel delivered between the centre and the customer delivery locations by 20%, and the CO_2 equivalent emissions per parcel delivered have also reduced by 54%. The trial emphasizes that even in a supply chain system in which goods are highly consolidated, the potential to achieve sustainability, reduce greenhouse gas emissions and total distance travelled inside cities. In addition, the system operated in the presented trial has a direct contribution in improving the air quality and reducing the noises.

2.3 Vehicle Routing Problem

The vehicle routing problem is the problem of finding the optimal set of routes to perform all transportation demands with a specific fleet, more precisely, managing which vehicle handles which customers and the sequence of visiting those customers in a way that minimizes the total cost or distance. The high interest of vehicle routing problem (VRP) is not only motivated by their complexity as optimization problems but also by their relevance to real-world application. As a consequence, the academic and industrial world focuses more on different variants of VRP. More than 70 years have elapsed since Dantzig and Ramser (1959) presented the first vehicle routing problem, at that time called the dispatching problem. The authors' concerned about finding the optimum between a bulk terminal and a large number of service stations supplied by the terminal routes for a fleet composed of gasoline delivery trucks. To solve the problem, the authors presented a simple matching-based heuristic. Clarke and Wright (1964) extend Dantzig and Ramser (1959) work and formulate a VRP with more restrictions and constraints like different vehicle capacities. The authors proposed a simple but effective heuristic to find a near-optimal solution.

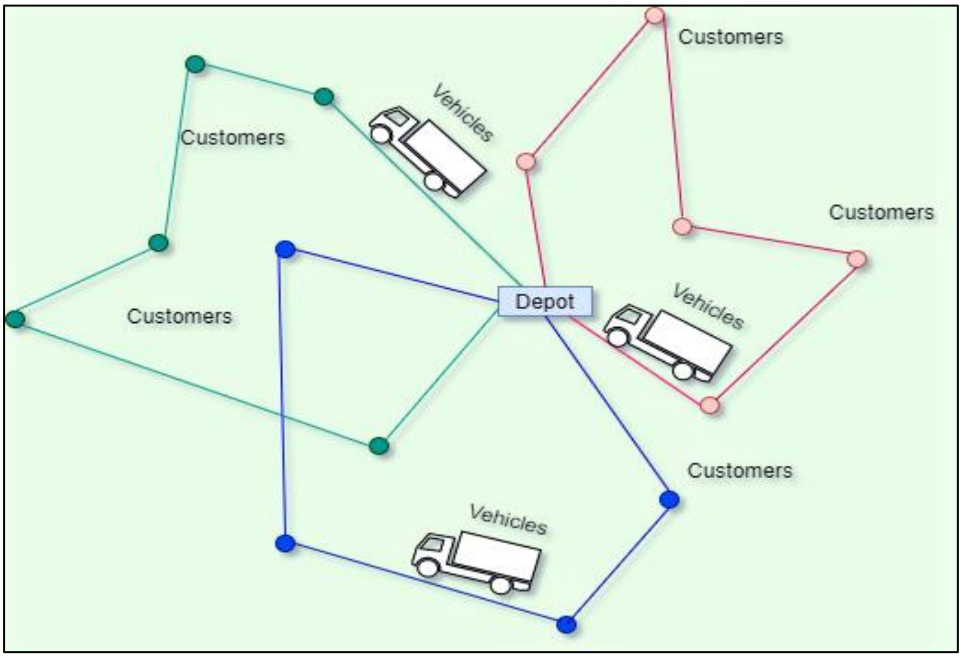


Figure 2.2: An example of vehicle routing problem presentation.

The vehicle routing problem is classified according different factors, but mainly:

- The network structure, where the operation is performed on the locations of the customers, which are identified as vertices of a graph called node routing problem. In contrast, the operations that are performed on the arcs are called the arc routing problem.
- The type of transportation requests, which is all the requests of all goods that are distributed from the depot to a set of customers. The main types are: delivery and collections, point-to-point transportation, alternative and indirect services, split and non-splits services, multimodal services, dynamic and stochastic routing
- The constraints, such as capacities, route length, time window, multiple use of vehicles
- The objective function, which can be a single objective optimization function, or multiple criteria optimization function.

Dantzig–Fulkerson–Johnson formulate the travelling salesman problem (TSP) as an integer linear program (Dantzig and Ramser, 1959), later on the formulation was extended to create a two index vehicle flow formulations to present the vehicle routing problem as shown below (Laporte, 1992a):

- Model formulation

On a graph G = (V, E) where V = {0,. . ., n} is the vertex set, and E = {(i, j)| i ≠j; i, j ∈ V} is the arc set. V represents the customers and the depot, where i=0 denotes 0, and vertices from i=1,…,n corresponds to the customers. C_{ij} present the costs of going from i to j, K is the number of vehicles, $r(s)$ present the minimum number of vehicles needed to serve set S and 0 denote the depot.

$$Min \sum_{i \in V} \sum_{j \in V} C_{ij} X_{ij} \tag{2.1}$$

S.t:

$$\sum_{i \in V} X_{ij} = 1 \; \forall j \in V\{0\} \tag{2.2}$$

$$\sum_{j\in V} X_{ij} = 1 \ \forall i \in V\{0\} \tag{2.3}$$

$$\sum_{i\in V} X_{i0} = K \tag{2.4}$$

$$\sum_{j\in V} X_{0j} = K \tag{2.5}$$

$$\sum_{i\notin S}\sum_{j\in S} X_{ij} \leq |S| - r(s) \tag{2.6}$$

$$X_{ij}\,\{0,1\} \ \forall\, i,j \in V \tag{2.7}$$

The objective function is to minimize the total costs. The first and second constraints denote that the number of vehicles entering each vertex must equal the number of vehicles leaving the vertex. Constraints (2.4, 2.5) ensure that the number of vehicles leaving the depot must equal the number of vehicles entering the depot. Constraint (2.6) is the sub tour elimination. While the last constraint shows the integrality constraints.

2.3.1 Vehicle routing problem classifications

Different variants of vehicle routing problem were discussed in the literature; such as vehicle routing problem with backhauls (VRPB), heterogeneous or mixed fleet (HFVRP), periodic vehicle routing problem (PVRP) and split delivery vehicle routing problem (SDVRP), In addition to the capacitated vehicle routing problem (CVRP).

The VRPB is concerned about delivering goods from depot to customers and vice versa, where the delivering of goods from depot to customers is known as linehaul, and the backhaul goods picked up from the customers to the depot. The HFVRP refers to a fleet of vehicles at the depot with different vehicle specifications, like capacity and distance range; it has been studied first by (Golden et al, 1984). PVRP is a variant where the customers require repeated visits with a planning time horizon. The SDVRP is concerned about visiting the same customer more than once to satisfy the customers demand (Irnich et al, 2014).

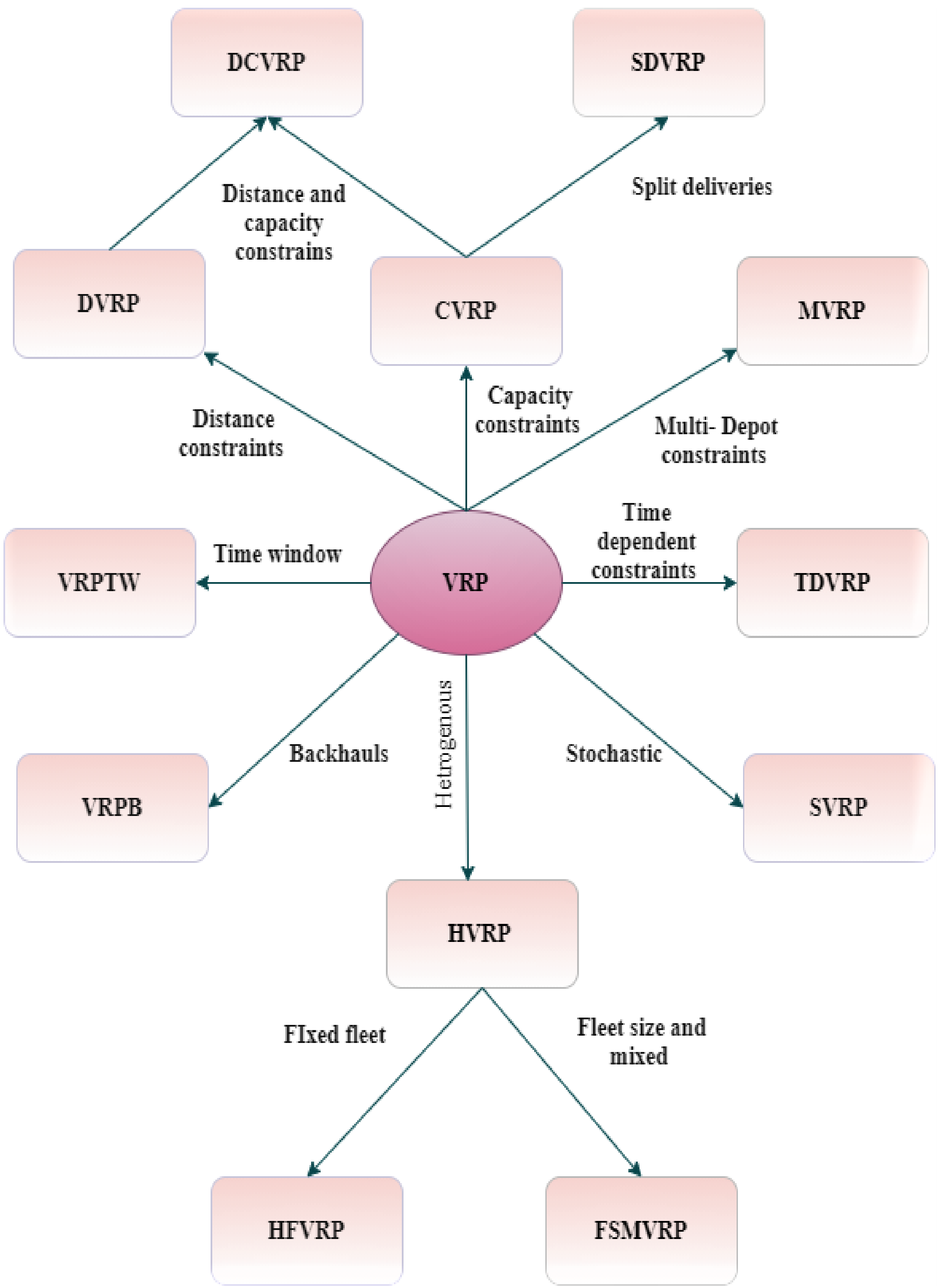


Figure 2.3: Vehicle routing problem variants.

The capacitated vehicle routing problem is one of the basic models in the vehicle routing problem family, which has been extensively studied in the literature. The problem can be described as follows; a set of m identical vehicles with identical capacities and are located at the depot, the objective is to determine a set of routes that satisfy all customer demand with least cost, so that each route does not exceed the vehicle capacity and that each customer visits only once. Time windows are a common extension in vehicle routing problem formulations where the service time of each customer is determined in advance. For illustrative purposes, the capacitated vehicle routing problem with time windows formulation is introduced here and it is an extension to the one presented in the previous section. On a graph G = (V, E) where V = {0,. . ., n} is the vertex set, and E = {(i, j)| i ≠j; i, j ∈ V} is the arc set. V represents the customers and the depot, where i=0 denotes 0, and vertices from i=1,…,n corresponds to the customers. Let a_i, b_i are time window for each customer $i \in V$, and τ_i is the start time of each customer service, s_i is the service time, and t_{ij} is the travel time from customer i to j. q_i presents the customer demand. Q_i denotes the capacity of the vehicle after leaving customer i, while G presented the vehicle capacity.

$$Min \sum_{i \in V} \sum_{j \in V} C_{ij} X_{ij} \tag{2.8}$$

S.t:

$$\sum_{i \in V} X_{ij} = 1 \ \forall j \in V/\{0\} \tag{2.9}$$

$$\sum_{j \in V} X_{ij} = 1 \ \forall i \in V/\{0\} \tag{2.10}$$

$$\sum_{i \in V} X_{i0} = K \tag{2.11}$$

$$\sum_{j \in V} X_{0j} = K \tag{2.12}$$

$$\sum_{i \notin \mathbf{S}} \sum_{\mathrm{j} \in \mathrm{S}} \mathrm{X_{ij}} \leq |S| - r(s) \tag{2.13}$$

$$X_{ij} \left(\tau_i + s_i + t_{ij} - \tau_j \right) \leq 0 , \qquad \forall i, j \in V \tag{2.14}$$

$$a_i \leq \tau_i \ \leq b_i, \qquad \forall i \in \{1,2, \dots, n\} \tag{2.15}$$

$$X_{ij}\,(Q_i + q_j - Q_j) \leq 0 \;\forall i, j \in V \tag{2.16}$$

$$Q_i \leq G \quad \forall i \in V \tag{2.17}$$

$$X_{ij}\,\{0,1\} \;\forall\, i, j \in V \tag{2.18}$$

Constraint (2.14) specifies the relationship between the service time of customer i and customer. Constraint (2.15) indicates the time window of customer i. Constraints (2.16, 2.17) are the capacity constraints, where constraint (2.16) ensure that the capacity of the vehicle after leaving customer i, is reduced by the value of customer i demand, and that the value of the vehicle's capacity after leaving customer i, doesn't exceed the capacity of the vehicle. Constraint (2.18) indicates the integrality constraints.

The distance constraint is another extension of the vehicle routing problem. In this variant the vehicles have limited driving range that cannot be exceeded during the route. Let the maximum driving range of vehicles denote by D_k, and $d_{ij}$the distance between customers. The constraint can be defined as follow:

$$\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ijk} \,.\, d_{ij} \leq D_k, \quad \forall k \;\in \{1,2,\dots,K\} \tag{2.19}$$

In general, vehicle routing problem (VRP) models are classified into three main levels according to their degree of realism as shown in Figure 2.4. The first one is the classical-basic VRP models, a theoretical problem, they mainly used to solve methods in controlled environments, and where their performance can be assessed before executing them in practical applications. Solving them can be done by exact or approximate methods. The classical advanced vehicle routing problem models are characterized by a higher level of realism; such as integrated routing and logistics, large-scale problems and multi-objective functions. The Rich VRP models are more complex, where metaheuristic algorithms used to solve them such as genetic algorithms, ant colony optimization, and local search.

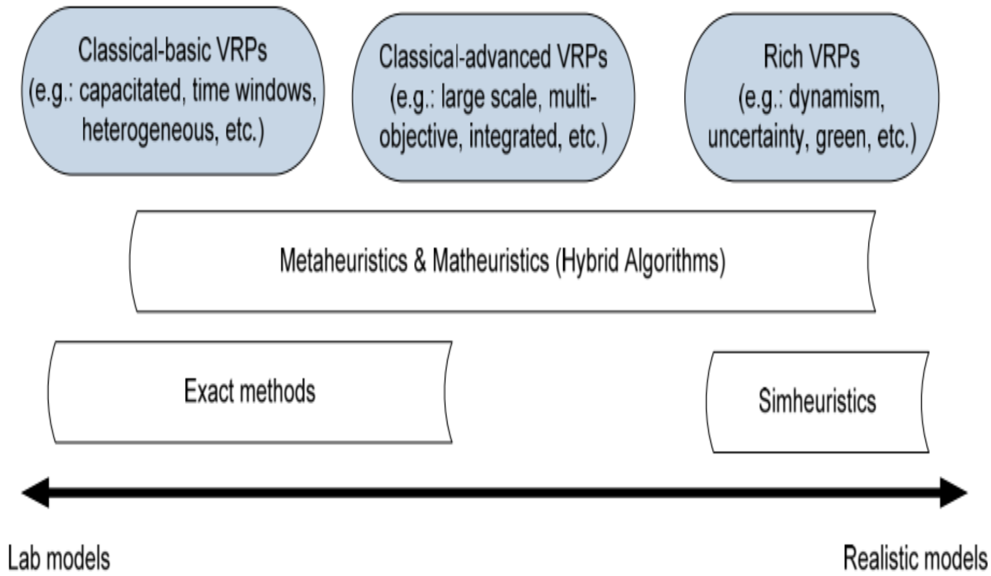


Figure 2.4: Classification of Vehicle Routing Problem (VRP) models according to their degree of realism (Caceres-Cruz et al, 2014).

2.3.2 Exact and heuristic method for the VRP

Vehicle routing problem is an NP hard problem, where exact approaches can only solve small instances. Few exact approaches introduced in the literature to solve VRP. Laporte (1992) classified exact approaches introduced in the literature into three classes:

- Direct tree-search methods
- Dynamic programming methods
- Integer linear programming methods.

Branch and Bound based on the following k-degree center tree was proposed early by (Christofides et al, 1981). They have successfully solved VRPs ranging in size from 10 to 25 vertices. Fisher and Jaikumar (1981)) improves Christofides et al. (1981) method by defining K-tree to be a set of n + K edges that span the graph. This algorithm improves the optimal solutions for a number of difficult problems with 100 customers for well-known problems and with 25–71 customers for several real problems (Eilon et al, 1974) was first to propose dynamic programming to solve vehicle routing problem. Only a few researches were presented in the literature to solve the vehicle routing problem using dynamic programming, since the problem is considered weak for large size problems. Balinski and Quandt (1964) was first to develop a set partitioning problem to solve VRP for truck delivery.

Route construction heuristics is a traditional heuristic approach that select nodes based on minimization criterion in a sequential way until a feasible solution is obtained (Bräysy and Gendreau, 2005), one of the most know heuristic is the savings heuristic of (Clarke and Wright, 1964) which was basically introduced to solve VRP problem. The other heuristic is the nearest neighbor heuristic, the routes start by finding the nearest un-routed customer to the depot, then finding the unrouted customer that is close to the last added one, until all unrouted customers are included. Sweep heuristic was proposed by (Gillett and Miller, 1974), Solomon (1987) was the first to solve vehicle routing problem with time window constraints using sweep heuristic, the logic behind the heuristic is to divided the problem, into clusters stages and scheduling stages (Bräysy and Gendreau, 2005). The parallel route building was proposed by Potvin and Rousseau (1993) This algorithm is based on the idea of initializing many routes at the same time (parallel), and uses a generalized regret measure to select the next unrouted customers for insertion. Improvement heuristics is based on improving the initial solution by performing neighborhood search iteratively. Most improvement algorithms are used for the vehicle routing problem such as string relocation and string exchange.

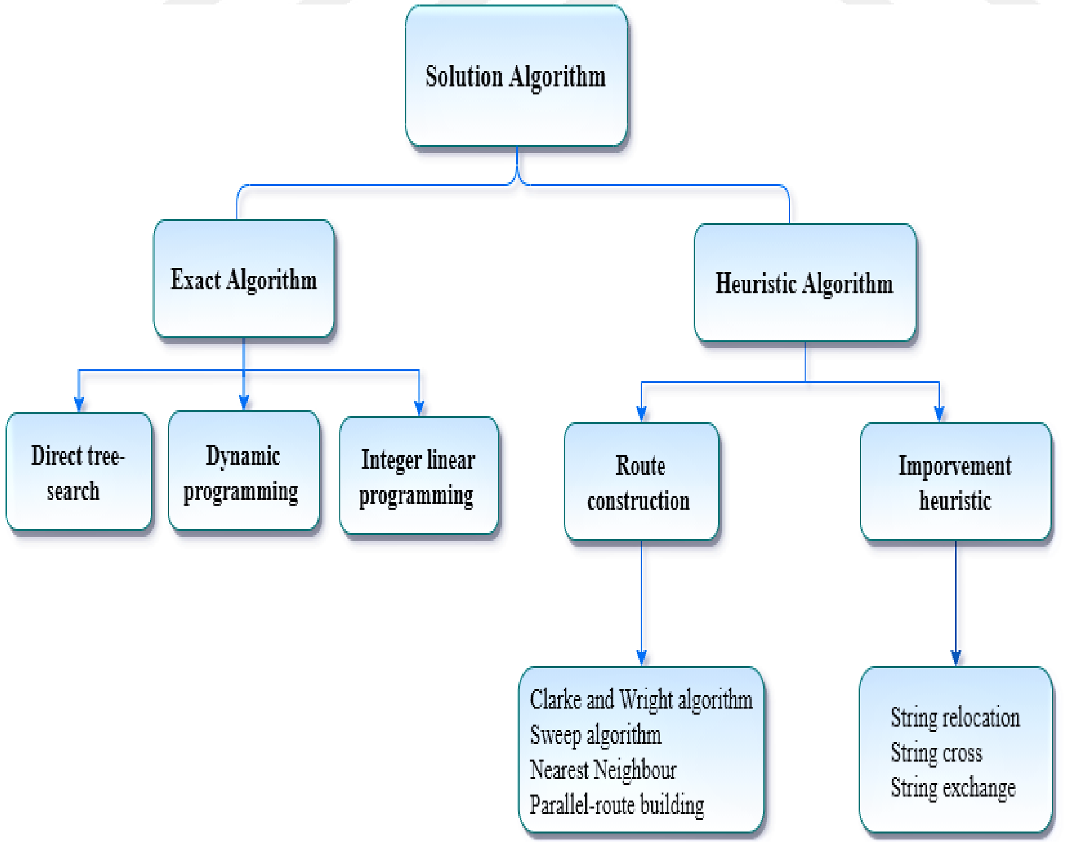


Figure 2.5: Solution algorithms for VRP.

2.4 Literature Review

In this section, abroad literature on mixed vehicle routing problem with time windows is first presented in section 2.4.1, followed by a review on replacement model in section 2.4.2.

2.4.1 The mixed vehicle routing problem with time window

Vehicle fleet composition can be found in the literature within two premier categories (Du et al, 2016; Etezadi and Beasley, 1983): (1) vehicle fleet size problems, which refer to the decision of determining the number of homogeneous fleet of vehicles, and (2) vehicle fleet composition problems, which refer to the problem of deciding the fleet size and mix simultaneously for a mixed fleet of vehicles. Fleet composition problems are usually discussed in combination with other transportation problems. Hoff et al. (2010) introduced a comprehensive literature review that discusses the industrial aspects of combined routing and fleet composition in maritime and road transportation. The authors classified the research articles related to this integration into four classes: fleet size mixed vehicle routing problem, heterogeneous fixed fleet vehicle routing problem, fleet size mixed vehicle routing problem with time windows, fleet size mixed vehicle routing problem with multiple depots. Golden et al. (1984) presented the first article that relaxed the homogeneous fleet assumption in vehicle routing problem, where different types of vehicles assumed to be available at the depot. Their formulation is classified as a fleet size and mix vehicle routing problem.

Van Duin et al. (2013) investigated the impact of routing constraints, electric vehicle characteristics and driving environment on the cost differences between electric and conventional commercial vehicles. They formulated the problem as a mixed integer programming model and then used sequential insertion heuristic to solve the problem. The authors have represented the vehicle acquisition costs as a daily fixed cost of the vehicle used. This approach, despite its simplicity, still requires analysis of different fleet mix scenarios, and restricts the use of the model for multi-period fleet investment decisions. Salhi et al. (2013) introduced fleet size and mixed vehicle routing problem with backhauls, the authors presented new ILP formulation to minimize the total cost of routes originating and terminating at the depot, taking into consideration the capacity and route length limitations. Sassi et al. (2015) handled a mixed fleet of electric and conventional vehicle routing problem, where different charging technologies and time dependent charging costs were considered. They introduced a charging routing heuristic to generate initial solutions as well as an inject-eject-based local search method with three different insertion strategies.

Rezgui et al. (2015) introduced the electric Modular Fleet Size and Mix Vehicle Routing Problem with Time Window, which is a new type of logistics scheme for urban freight delivery that takes into account the possibility of recharging at a customer location. As a solution method, the authors developed an approach based on a genetic algorithm. The experimental results obtained on benchmarks from the literature show that with the modularity feature, using electric vehicles for freight delivery in urban environments is economically interesting. Li et al. (2016) formulate mixed bus fleet management (MBFM) taking into consideration four different types of buses (compressed natural gas bus, diesel bus, electric bus, hybrid-diesel bus) in order to solve the problem, the authors presented a new approach new life additional benefit-cost (NLABC) which aims maximizing the total net benefit. The presented formulation allowed them to determine the optimal fleet size and composition, while including the routing problem.

Macrina et al. (2019) modeled a mixed vehicle fleet composed of EVs and CVs, where partially recharging the EVs was allowed. The authors proposed an iterated local search metaheuristic to solve the formulated model. Several computational experiments on modified benchmark instances were conducted. They concluded that the use of partial recharge may lead to more effective and sustainable solutions. Hiermann et al. (2019) introduced a mix of conventional, hybrid, and electric vehicles routing problem. They designed a hybrid genetic algorithm to solve the problem. Rezgui et al. (2019) presented a fleet size and mix vehicle routing problem with EV modular to achieve sustainable urban freight deliveries. The modules can be released at customer's locations to overcome length restrictions in some urban areas, to recharge the battery or to help respect delays when performing the tours. Alizadeh Foroutan et al. (2020) considered a green vehicle routing and scheduling problem with heterogeneous fleet including reverse logistics in the form of collecting returned goods along with weighted earliness and tardiness costs. To find near-optimal solutions simulated annealing (SA) and a genetic algorithm (GA) were suggested and evaluated with respect to two considered criteria, solutions quality, and computational times. Goeke and Schneider (2015) optimize the routing of a mixed vehicle fleet consisting of electric commercial vehicles (ECVs) and conventional internal combustion commercial vehicles (ICCVs). In contrast to the existing routing models, the presented model utilizes a realistic energy consumption model that incorporates speed, gradient and cargo load distribution. An Adaptive Large Neighborhood Search algorithm that is enhanced by a local search for intensification was developed. Lebeau et al. (2015) formulated a fleet size and mix vehicle routing problem with time windows for electric vehicles integrated with the energy consumption model, so that variable range of electric vehicles can be considered. The authors investigate different vehicle's sizes with either electric propulsion or internal combustion engine vehicles. Those vehicles vary in costs, payload, energy consumption and many more. In their study the authors considered different aspects of the problem, such as the fast charge of electric vehicles at the depot, time window and range constraints.

Mouhrim et al. (2018) presented a mixed integer linear programming to model a vehicle routing problem with a mixed fleet of electric and conventional vehicles with time window and capacity constraints, and two limitations; the conventional vehicles are limited with a fixed quantity of greenhouse gas emissions, and the electric vehicles are limited with range. Schiffer et al. (2021) developed a new methodology to analyze the comparative competitiveness between conventional and electric vehicles, by combining the calculations of total cost of ownership with a rich location-routing model. The authors presented an integrated model that takes into account strategic network design and operational routing decisions over multiple periods.

The presented model in this thesis is an extension to the one presented by (Lee et al. 2008). The authors present a vehicle mix fleet problem with a single depot denote by (0) and a set of N customers, $d_{ij}$the distance between customers, k type of vehicles, G_k is the capacity of vehicle from type k, q_i is the customer's demand, two decision variable are presented: X_{ijk}, Y_{ij}. When the vehicle travel over the arc between i, j, X_{ijk} equal 1 otherwise zero, Y_{ij} present the vehicle load from customer i to j. The objective function is to minimize the operation costs for a set of heterogeneous vehicles:

$$\sum_{k=1}^{K}\sum_{i=0}^{N}\sum_{j=0}^{N} o_k \,.\, d_{ij}.\, X_{ijk} \tag{2.20}$$

S.t:

$$\sum_{k=1}^{K}\sum_{i=0}^{N} X_{ijk} = 1, \quad \forall j \in \{1,2,\dots,N\} \tag{2.21}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{N} X_{ijk} = 1, \qquad \forall i \in \{1,2,\dots,N\} \tag{2.22}$$

$$\sum_{i=0}^{N} X_{ijk} = \sum_{l=0}^{N} X_{jlk}, \quad \forall j \in \{1,2,\dots,N\}, \;\forall k \in \{1,2,\dots,K\} \tag{2.23}$$

$$\sum_{i=0}^{N} Y_{ij} - \sum_{l=0}^{N} Y_{jl} = q_j, \;\forall j \in \{1,2,\dots,N\} \tag{2.24}$$

$$\sum_{i=1}^{N} Y_{i0} = 0 \tag{2.25}$$

$$\sum_{j=1}^{N} Y_{0j} = \sum_{i=1}^{N} q_i \tag{2.26}$$

$$Y_{ij} \le \sum_{k=1}^{K} G_k \,.\, X_{ijk}, \;\forall i,j \in \{1,2,\dots,N\}, i \neq j \tag{2.27}$$

$$Y_{ij} \ge 0, Y_{ii} = 0, X_{ijk} \in \{0,1\} \tag{2.28}$$

Constraints (2.21, 2.22) ensure that each customer is served once by one vehicle from any type. Constraint (2.23) implies that the vehicle entering each customer, should leave that customer. Constraint (2.24) ensures that the demand of each customer has to be satisfied. Constraint (2.25) guarantees that all vehicles from all types should return back to the depot empty. Constraint (2.26) shows that the sum of all deliveries in all vehicles is equal to the sum of all customers' demand. Constraint (2.27) is the capacity constraints, where the vehicle load from customer i to customer j should not exceed the vehicle's capacity. And the last constraint refers to the non-negativity of the decision variable Y_{ij} and that X_{ijk} is a binary decision variable.

2.4.2 Fleet replacement model

Previous studies have discussed different aspects of replacement models, which mainly involved two types of models: serial and parallel replacement models. In the serial models the decision is made for a single asset, so each time a replacement decision is made the assets will be replaced by an identical asset. Therefore, they are economically independent. For example, Chand & Sethi. (1982) introduced machine replacement model under technical environmental improvement over time. Hopp & Nair (1991) provided more advanced technology, but the appearance times of future technologies are unknown. For more on this literature, see (e.g. Refs. Bean et al, 1994).

In contrast, the parallel replacement model refers to assets that are economically interdependent and operate in parallel. Vander Veen & Jordan. (1989). A number of studies in the literature investigate the parallel replacement models. Karabakal et al. (1994) formulated a deterministic rationing replacement problem as a zero-one integer program. They developed an optimization algorithm using Lagrangian relaxation methodology where a new multiplier adjustment method was used to solve one of the Lagrangian dual. Hartman (2000) introduced a deterministic parallel replacement problem with economies of scale in purchases under demand and capital budgeting constraints. The author formulated an integer programming model and solved it for a number of scenarios presented to provide better understanding of various replacement problems. Hartman (2000) also studied the replacement model under the effect of utilization using stochastic dynamic programming formulation. The author obtained a replacement policy depending on the asset's age and cumulative utilization. More analysis on the same problem was provided by (Hartman and Ban, 2002). The authors presented an integer program formulation for series- parallel flow shop configuration to determine the optimal decisions for each asset over a finite time horizon. The model was difficult to solve; therefore, valid inequalities were provided to improve the lower bound by linear programming relaxation, and dynamic programming was introduced to develop upper bounds for the problem. The use of fuzzy sets in studying the replacement decisions was discussed in many researches. Baskak & Kahraman (1998) examined the life of the defender by a membership function; which presents the intersection of the membership functions regarding the physical impairment of the defender, its obsolescence, and extreme economic conditions. Chang (2005) presented a fuzzy approach for equipment replacement where the current equipment costs and market obsolescing investigated fuzzily. Two numerical examples were provided to prove the usefulness of fuzzy strategic replacement as an extension to the traditional one.

Keles and Hartman (2004) studied the replacement decision for a heterogeneous bus fleet, where there are multiple challengers for each period of the planning time horizon. The authors also include the fixed costs and budgeting constraints in their investigation. Kleindorfer et al. (2012) formulated an optimal renewal decision model to adopt electric vehicles in the delivery fleet for mail and parcel distribution. The authors also examined the uncertainty about the fuel future price, electric vehicles battery costs and the total cost of fleet renewal over a 15 years' time horizon, which resulted in formulating an optimal strategy for EV adoption for La Poste, and support negotiations with major stakeholders. Parthanadee et al. (2012) analyzed the impact of the five common replacement rules on parallel replacement model under a user preference utilization pattern. They solved small numerical examples optimally under different scenarios, where actual data used to estimate the model parameters. They also examined different vehicle technologies, such as compressed natural gas or liquefied petroleum gas. Islam and Lownes (2019) designed a model to find the optimum bus replacement strategy and provide an optimum fleet consisting of hybrid electric and battery electric vehicles including charging infrastructure. Figliozzi et al. (2012) proposed a vehicle replacement model for a set of heterogeneous fleet vehicles, to evaluate environmental and policy issues such as greenhouse gas (GHG) taxes and fiscal incentives for purchasing electric vehicles. The authors also analyzed the impacts of utilization, the current engine technologies, fuel prices, and market conditions on purchasing decisions. They concluded that, for EVs to be competitive, tax incentives are needed with relatively moderate fuel prices. Another comprehensive assessment of the competitiveness of electric vehicles was presented by (Ahani et al, 2018). The authors developed a new optimization framework for vehicle replacement decision plan in order to derive an optimal combination of electric and conventional vehicles in urban freight transport. The presented framework is based on the concept of portfolio theory, with an objective function to minimize the total cost and the variance associated with some of the uncertain parameters of the total cost. Emiliano et al.(2020) formulated a fleet replacement model that integrates budget and environmental constraints together. The authors investigate their model on a set of diesel buses with different sizes, ages, maintenance costs and emissions rates, with an objective function to minimize the purchasing, operation cost (fuel) and maintenance costs over a time horizon of 50 years. The results show that it is possible to reduce the CO_2 emissions resulting from using diesel buses with a low annual budget.

Our presented model is an extension to the one presented by (Feng and Figliozzi, 2013), the authors formulated a fleet replacement optimization framework to analyze the economic and technological factors affecting the use of electric vehicles by introducing a wide range of scenarios. Three decision variables were introduced; P_{jk}, Y_{ijk}, X_{ijk}, they present the number of age i, year j, type k, purchase, salvage, used, respectively. The main parameters are defined as follow: u_{ik} indicate the annual mileage. v_k is the purchase cost of a new vehicle type k. while b_j is the budget at the beginning of year j. d_j is the demand of year j. h_{0k} presents the number of initial new vehicles.

The life cycle cost consists of three terms, each of them present the future costs for a set of vehicles and they assumed to be a known function of vehicle type and age:

$$\sum_{j=0}^{T-1}\sum_{k=1}^{K} v_k . P_{jk} . (1+dr)^{-j} - \sum_{f=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{ik} . Y_{ijk} . (1+dr)^{-j} + \sum_{i=0}^{A_k-1}\sum_{j=0}^{T-1}\sum_{k=1}^{K} [O_{ijk} + m_{ik} + e_{ik}] . u_{ik} . X_{ijk} . (1+dr)^{-j} \tag{2.29}$$

The first term presented the purchasing cost, where purchase cost of a type-k truck (\$) denotes by v_k, the second term is the salvage revenue as s_{ik} is the salvage revenue of a truck type k age i. The third term specifies the operation (O_{ijk}), maintenance (m_{ik}), and CO_2 emissions costs (e_{ik}) which are related to the number of used vehicles in age i, type k at year j.

The constraints:

$$\sum_{k=1}^{K} v_k \,.\, P_{jk} \leq b_j \quad \forall j \in \{0,1,2,\dots,T-1\} \tag{2.30}$$

$$\sum_{i=0}^{A_k-1} \sum_{k=1}^{K} X_{ijk} . u_{ik} \geq d_j \quad \forall j \in \{0,1,2,T-1\} \tag{2.31}$$

$$P_{0k} + h_{0k} = X_{00k}\,, \qquad \forall k \in \{1,2,\dots,K\} \tag{2.32}$$

$$X_{i0k} + Y_{i0k} = h_{ik}\;, \quad \forall i \in \{1,2,\dots,A_{k,}\}, \forall k \in \{1,2,\dots,K\} \tag{2.33}$$

$$P_{jk} = X_{0jk}, \qquad \forall j \in \{1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{2.34}$$

$$X_{(i-1)(j-1)k} = X_{ijk} + Y_{ijk}, \forall i \in \{1,2,.,A_k\}, \forall j \in \{1,2,.,T\}, \forall k \in \{1,2,..,K\} \tag{2.35}$$

$$X_{iTk} = 0, \qquad \forall i \in \{0,1,2,\dots,A_k-1\}, \forall k \in \{1,2,\dots,K\} \tag{2.36}$$

$$X_{A_k jk} = 0\;, \qquad \forall j \in \{0,1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{2.37}$$

$$Y_{0Jk} = 0\;, \qquad \forall J \in \{0,1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{2.38}$$

$$P_{jk}, X_{ijk}, S_{ijk} \in \{0,1,2,\dots\} \tag{2.39}$$

Constraint (2.30) ensures that the cost of purchasing new vehicles from any type should not exceed the budget of that year. Constraint (2.31) implies that the total traveled distance by all used vehicles should not be lower than the annual demand. Constraint (2.32) shows that the number of used vehicles at the beginning of the time horizon should equal the initial new vehicles and the newly purchased ones. While constraint (2.33) implies that the initial number of vehicles of any type or any age (h_{ik}) should be equal to the number of used and salvaged vehicles. Constraint (2.34) insures that the new purchased vehicles at any year should be used immediately, and constraint (2.35) illustrate that after each year vehicles are either salvaged or used in the upcoming year Constraints (2.36, 2.37) show that the vehicles can't be used after they reach their maximum age A_k or period T which is the last year in the planning time horizon, while constraint (2.38) indicates that every new purchased vehicle should be used at least once before it is sold. And the last ensures that all decision variables take only non-negative integer values.

2.4.3 Literature gap

The operational cost plays a significant role in finding the best replacement policy for a set of vehicles along with vehicle characteristics, planning time horizon, annual utilization (mile traveled per year), and annual budget. And since we are presenting vehicles from different types; electric and conventional, the vehicles vary in their running costs, where the running cost for electric vehicles is way lower than that of conventional vehicles.

Previous published work included the one presented by (Feng and Figliozzi, 2013) assumed a mixed fleet with constant transportation costs, which depends on vehicles' age only. This approach, despite its simplicity may provide unrealistic solutions for real life situations, where the operational cost is affected by many factors including the routing constraints such as distance constraints, and the number of vehicles available at the depot. To define the problem precisely, we developed an integrated model considering both routing and fleet composition decisions in order to determine the best replacement policy for a set of electric and conventional vehicles in urban freight over a specific time horizon, where the operational cost is calculated using mixed vehicle routing problem with time windows (MVRPTW) for all possible fleet compositions in the replacement model. The results are used as inputs in the replacement model along with the other economic factors (salvage cost, purchase cost, discount rate), vehicle characteristics, initial fleet, annual budget, and annual utilization.

In today's competitive industry, it is important for companies to operate at the highest level of efficiency, so that customers are satisfied with the presented service, and the company makes profits. Fleet management for companies that depend mainly on transportations considered to be extremely important in order to minimize the total cost, and increase efficiency. Furthermore, fleet management supports settling on choices with respect to future investment. Fleet management techniques in urban freight are structured in a way that is suitable for conventional vehicles, where the driving range and refueling time are not considered. Those techniques are mainly concerned about managing fuel consumption, maximizing vehicle utilization and controlling factors that may affect the delivery operations.

The approach for mixed fleet is to use techniques that have been developed for conventional vehicles. These techniques may fall short in managing fleets with electric vehicles effectively, due to additional constraints induced by the specific characteristics of electric vehicles, such as limited driving range. Moreover, the routing decisions determine the operational characteristics of the fleet, which is an important constraint in fleet composition decisions.

An illustration of how operational planning changes the fleet investment decisions is given in a simple example problem shown in Figure (2.6.a). This example includes only a single depot and three demand points, where the numbers above the arrows refer to the distances.

Figure (2.6.b) gives the optimal route for a conventional vehicle (CV) under no additional restrictions. The vehicle begins its tour at the depot, visits a set of customer points, and returns to the depot. The optimal route is 14 units. For a hypothetical EV with a range of 12 units, the route for the same customer points is 19 units as shown in Figure (2.6.c). Finally, figure (2.6.d) shows the realisation of the route if an EV is used with the CV's optimal route. The route is now 20 units.

This example above emphasizes the importance of planning decisions of a fleet composed of electric and conventional vehicles through three main points:

1. Applying the average mileage obtained from CV routing experiences directly to EV investment decisions may result in underestimating the costs of EVs, thus, may lead to wrong conclusions.
2. In addition, using the routes planned for CVs (by habit or planning) but adjusting the average mileage value according to range restrictions may result in overestimating the costs of EVs.
3. Furthermore, using daily projections of fixed costs does not solve the integrated decision problem for a mixed vehicle fleet. Therefore, the optimal solution will still require a scenario analysis for all combinations of vehicle numbers for different vehicle types.

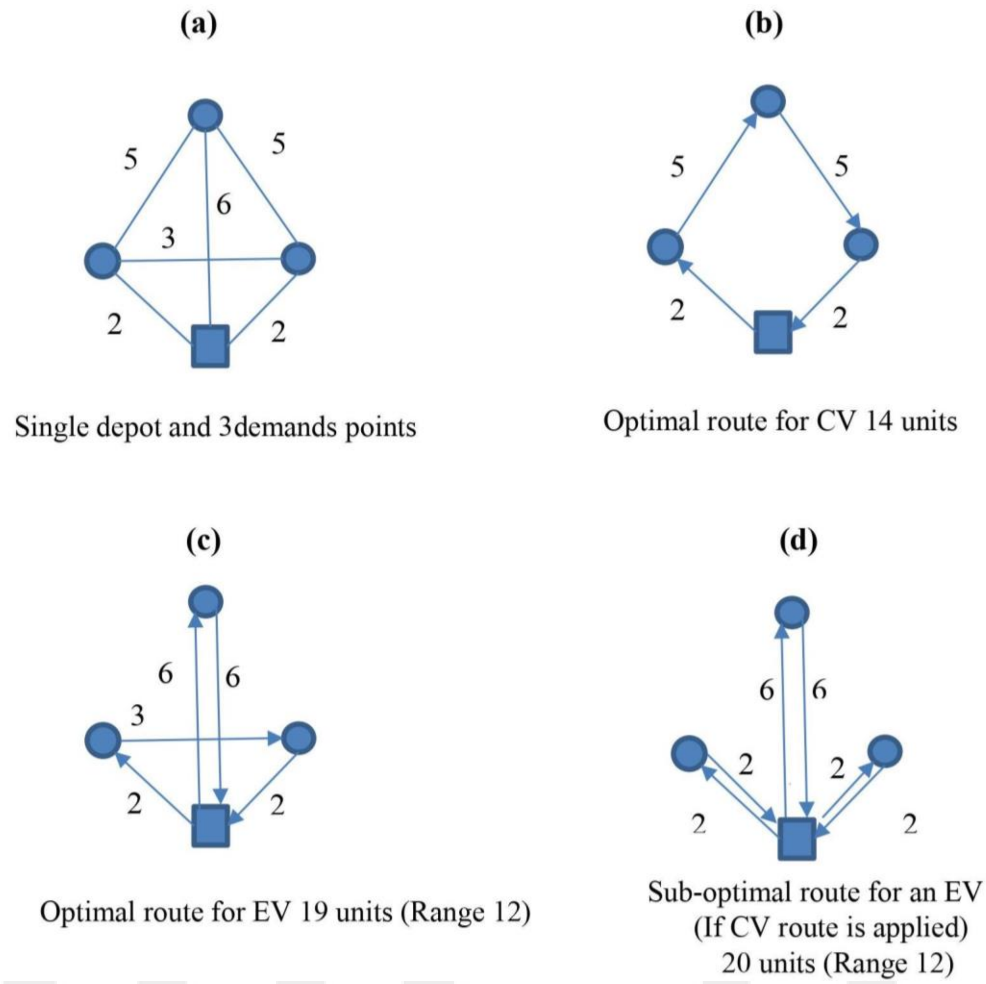


Figure 2.6: Illustrative example of different solutions for VRP with different sets of vehicles.

3. METHODOLOGY AND MATHEMATICAL MODELS

This chapter begins with an explanation of the research methodology which is conducted to achieve the research aims and goals. This is followed by the two mathematical models that have been developed and used throughout the thesis work: the replacement model, and fleet size and mixed vehicle routing problem with time window. The methodology flow chart presented at the end of section 3.1 illustrates how we integrated the two models.

3.1 Methodology

The replacement model is a classical topic that has been solved using different techniques. Perhaps the dynamic programming was among the most used ones, since most of the problem in the literature considered a replacement model with homogeneous assets (identical assets) (Jin and Kite-Powell, 2000), some problems was extended so that the uncertainty was considered, in such a problem the stochastic dynamic programming was used. Whereas, when the assets used in the study were heterogeneous (assets with different specifications), integer programming was the approach to use. In this thesis an integer programming vehicle replacement model is used to evaluate the performance of electric vehicles in heterogeneous fleets.

In this thesis, we proposed an integrated model to investigate the planning of a mixed fleet of electric and conventional vehicles under routing and replacement consideration. Where, we used two dependent models; mixed vehicle routing model with time window (MVRPTW) and replacement model to determine the optimal fleet replacement policy for a set of electric and conventional fleets. The MVRPTW model is responsible for minimizing the sum of the operational costs incurred depending on the vehicle type chosen and the travelled distance. Therefore, all possible fleet compositions for the initial fleet of electric and conventional vehicles are generated. Then, a MVRPTW is used to determine the minimum operation cost for each one of those compositions. Thereafter, the results are inserted as an input into the replacement model, so that the operation cost for any fleet composition occurring over the planning time horizon in the replacement model is known. Figure 3.1 shows the presented methodology.

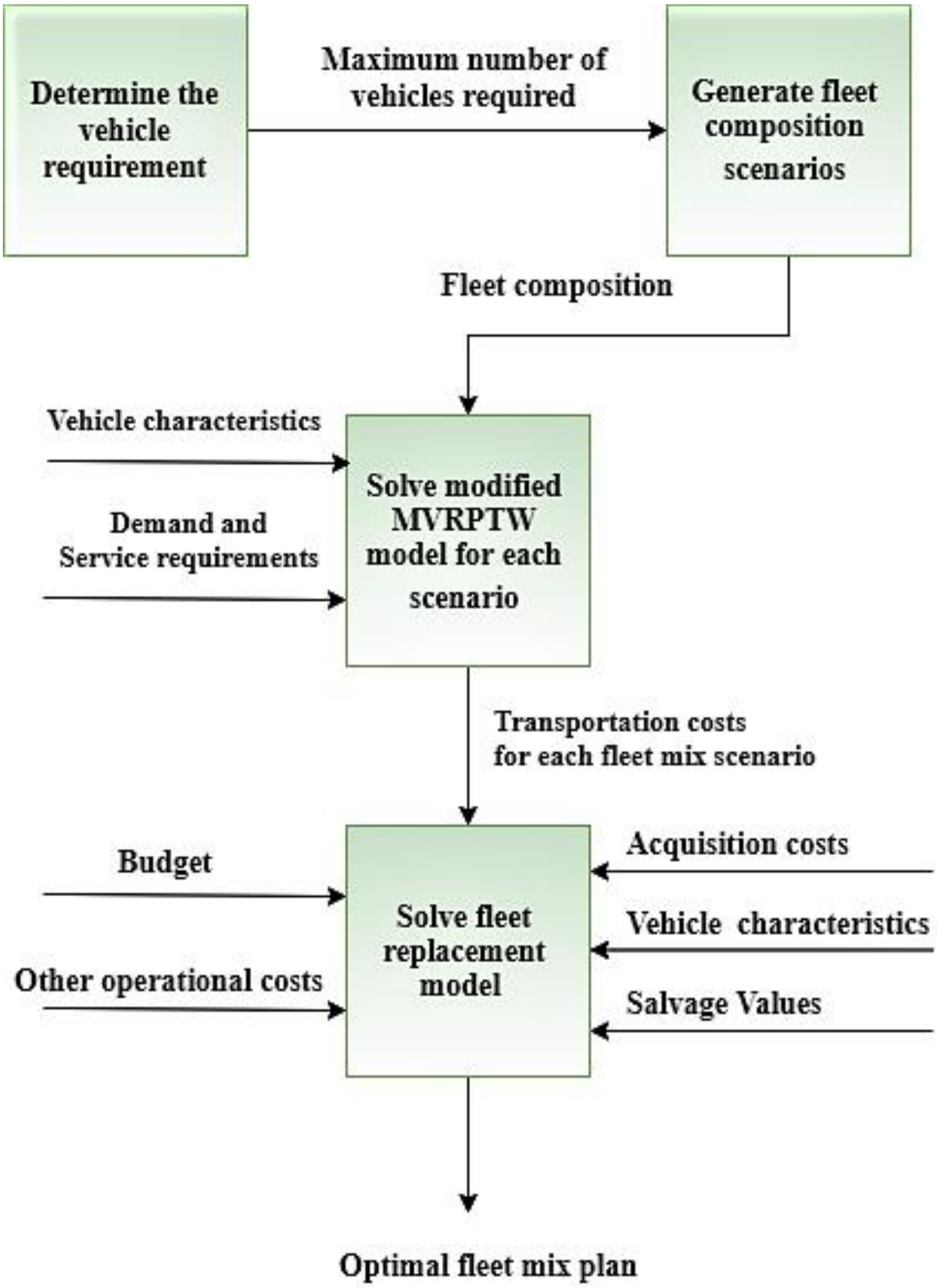


Figure 3.1: The general structure of the proposed approach.

At the beginning the vehicle requirement is determined. Then, a number of scenarios are generated for all possible fleet compositions of electric and conventional vehicles. After defining the vehicle characteristics and demand, a mixed vehicle routing model with time windows is used to calculate the operation cost. The results are inserted as an input in the replacement model. The replacement model has many other inputs along with the operational cost, like future economic factors (such as salvage value, purchased cost, maintenance costs, CO_2 emissions costs and the taxes), initial fleet composition, vehicle characteristics, and budget to obtain the best replacement policy for a set of mix fleet of electric and conventional vehicles.

3.2 Mathematical Models

In the basic model, the operation cost was calculated in terms of constant transportation costs, which may depend on the vehicle's age. The major change in the presented formulation is that the operation cost calculated using fleet size and mixed vehicle routing model with time window. In this section, we expose the mathematical formulations for both models we used to investigate our problem.

3.2.1 Replacement model

The replacement model decides the optimal time to replace the used vehicles with new vehicles under budget and demand constraints over a specific time horizon. The replacement model is economically interdependent, that means, taking a decision for one vehicle affects the other vehicles. More precisely, if one vehicle is salvage, there must be another vehicle purchased at the same year. Six types of costs were considered in the presented model: The purchase cost, salvage cost, operation cost, maintenance cost, CO_2 emissions cost, and fuel taxes cost. Decision variables for the number of vehicle purchased (P_{tk}), used (W_{ftk}) and salvaged (R_{ftk}) are presented to formulate the problem.

Before formulating the problem, some assumptions have been made and they are mentioned below:

- The annual demand and budget should be defined in advance.
- The annual demand and budget are fixed over the entire planning time horizon.
- The annual utilization is not a function of the vehicle's age.
- The length of the planning time horizon should have to be predefined.

A list of indices, decision variables, and parameters used in the model are given below:

- **Indices**

Age of a type k truck in years $f \in \{0,1,2,\dots,A_k\}$

Time periods t $\in \{0,1,2,\dots,T\}$

Type of truck/engine k $\in \{0,1,2,\dots,K\}$

- **Decision Variable**

W_{ftk} The number of age- f, type-k vehicles used in year t, $W_{ftk} \in \mathbb{Z}^+$

R_{ftk} The number of age- f, type-k vehicles salvage at the end of year t, $R_{ftk} \in \mathbb{Z}^+$

P_{tk} The number of new type-k vehicles purchased at the beginning of year t, $P_{tk} \in \mathbb{Z}^+$

- **Parameters**

v_k The purchasing cost of a type k truck in dollars.

s_{fk} The salvage value of an age f type-k vehicle. where $s_{0k} = v_k$

Q_{fk} Maintenance cost of age f type k vehicle per mile.

e_{fk} CO_2 emissions cost rate of age f type k vehicle per mile.

F_{fk} Fuel tax cost of age f type k vehicle per mile.

B_t Budget at the beginning of year t.

D_t Annual miles that needs to be traveled at year t.

h_{fk} Initial number of age f , type k vehicle at the beginning of the time horizon.

u_{fk} Utilization of age f , type k vehicle.

dr Discount rate.

- **The objective function and constraints:**

Min V=

$$\sum_{t=0}^{T-1}\sum_{k=1}^{K} v_k.P_{tk}.(1+dr)^{-t} - \sum_{f=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{fk}.R_{ftk}.(1+dr)^{-t} + \sum_{t=0}^{T-1} Z(M_{t1},M_{t2}).(1+dr)^{-t}$$

$$\sum_{f=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}[Q_{fk}+e_{fk}+F_{fk}].u_{fk}.W_{ftk}.\left(1+dr\right)^{-t} \tag{3.1}$$

Subject to:

$$\sum_{k=1}^{K} v_k.P_{tk} \le B_t \quad \forall t \in \{0,1,2,\dots,T-1\} \tag{3.2}$$

$$\sum_{f=0}^{A_k-1}\sum_{k=1}^{K} W_{ftk}.u_{fk} \ge D_t \quad \forall t \in \{0,1,2,T-1\} \tag{3.3}$$

$$P_{0k}+h_{0k}=W_{00k}, \qquad \forall k \in \{1,2,\dots,K\} \tag{3.4}$$

$$W_{f0k}+R_{f0k}=h_{fk}, \quad \forall f \in \left\{1,2,\dots,A_{k,}\right\}, \qquad \forall k \in \{1,2,\dots,K\} \tag{3.5}$$

$$P_{tk}=W_{0tk}, \qquad \forall t \in \{1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{3.6}$$

$$W_{(f-1)(t-1)k}=W_{ftk}+R_{ftk} \quad \forall f \in \{1,2,\dots,A_k\}, \forall t \in \{1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{3.7}$$

$$W_{fTk}=0, \qquad \forall f \in \{0,1,2,\dots,A_k-1\}, \forall k \in \{1,2,\dots,K\} \tag{3.8}$$

$$W_{A_k tk}=0, \qquad \forall t \in \{0,1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{3.9}$$

$$R_{0tk}=0, \qquad \forall t \in \{0,1,2,\dots,T\}, \forall k \in \{1,2,\dots,K\} \tag{3.10}$$

$$M_{tk}=\sum_{f=1}^{A_k-1} W_{ftk}, \quad \forall t \in \{0,1,2,\dots,T\}, \mathrm{k} \in \{1,2,\dots,K\} \tag{3.11}$$

$$u_{fk} = \left(\sum_{i=0}^{N} \sum_{j=0}^{N} d_{ij} \Big/ \sum_{t=0}^{T-1} W_{ftk} \right). C, i \neq j, \forall f \in \{1,2, \dots, A_{k-1,}\}, \mathrm{k} \in \{1,2, \dots, K\} \qquad (3.12)$$

$$P_{tk}, W_{ftk}, R_{ftk} \in \{0,1,2, \dots\} \qquad (3.13)$$

The objective function minimizes the total cost for the set of vehicles over the planning horizon. The first and second terms in the cost function present the purchasing and salvage value. The third term indicates the operational cost, which is obtained using Fleet Size and Mixed Vehicle Routing Model, while the fourth term refers to the costs of maintenance, CO_2 emissions, and the fuel cost. Constraint (3.2) ensures that the cost of purchasing new vehicles from any type should not exceed the annual budget. Constraint (3.3) implies that the total traveled distance by all used vehicles should not be lower than the annual demand. Constraint (3.4) shows that the number of used vehicles at the beginning of the time horizon should be equal to the initial new vehicles and the newly purchased ones. Constraint (3.5) implies that the initial number of vehicles of any type or at any age should be equal to the number of used and salvaged vehicles. Constraint (3.6) restricts the newly purchased vehicles at any year to be used immediately. Constraint (3.7) guarantees after each year vehicles are either salvaged or used in the upcoming year. Constraints (3.8, 3.9) ensure that vehicles cannot be used after they reach their maximum age A_k or period T which is the last year in the planning time horizon. Constraint (3.10) ensures that every new purchased vehicle should be used at least once before it is sold. Constraint (3.11) guarantees that the number of available vehicles of type k at time t equals the number of used vehicles. Constraint (3.12) makes the annual utilization equal to the average total distance traveled by all used vehicles multiplied by the annual working days. The last constraint ensures that all decision variables take only non-negative integer values.

Now, in order to determine the operational cost in the replacement model $Z(M_{t1}, M_{t2})$, a fleet size and mixed vehicle routing problem with time window is used. The fleet size and mixed vehicle routing problem with time window is discussed in the following section.

3.2.2 MVRPTW

In this section we address the problem of fleet size and mixed vehicle routing problem with time window. The complexity of this problem can be recognized in different ways, such as mixed vehicles, different operation range, and limited number of vehicles. The main characteristic of this problem is discussed below:

- Depot: is one of the main components in the vehicle routing problem, the vehicles start their routes from the depot and finish at the depot. There can be single or multiple depots within the problem, in our presented model, all customers served form a single depot. Also we assumed that refueling of conventional vehicles and recharging of electric vehicles happens at the depot; whenever a vehicle visits the depot it refuels and recharges to its maximum capacity.
- Customers: each problem has a set of customers to be served, the locations of the customers usually presented in a symmetric d×d matrix, the travel time between customers is also given.
- Vehicles: The fleet of vehicles available at the depot is set to be a mixed of electric and conventional vehicles, which means that the vehicles have different characteristics.

The mathematical formulation of the problem can be described as follows: we have a single depot indicated by index (0) and N customers. Each customer has a demand q_i which can be filled by any vehicle from any type. The distance between customers is defined by d_{ij}, and L_{ij} is the travel time between customers i and customer j. There are K types of vehicles and the number of vehicles is limited. G_k denotes the capacity of vehicle and H_k denotes the operational range of vehicles. The decision variable X_{ijk} equal to 1 when the vehicle k from any type travels from customer i to j and zero otherwise. U_{ik} the load of vehicle k after visiting customer i ,while Y_{ij} is the vehicle load from the customer i to j.

- **Constraints on customer's demands**

Exhaustive list to all the constraints related to the demand of the customers are discussed below:

- Every customer has a demand q_i and must be served once and only once by a vehicle of any type.
- The Customers orders can vary in size and weight.
- Each customer request should be fulfilled within a given time window, this time window varies from one day to a whole time horizon.

- **Constraints on vehicles**

As we present a mixed of electric and conventional vehicles, different constraints on vehicles has been set:

- The number of vehicles of any type is limited.
- The travelled distance for each vehicle type is restricted.

- **Assumptions:**
  - There is a single depot (index 0) and N customers.
  - The refueling of conventional vehicles and recharging of electric vehicles happens at the depot; whenever a vehicle visits the depot it refuels and recharges to its maximum capacity.
  - The customer's locations are known in advance.
  - The demand is deterministic and known for each customer.
  - The speed is constant for both electric and conventional vehicles over a link.
  - The vehicle begins and finishes its route at the depot.
  - There are K types of vehicles located at the depot.
  - The required service time is known in advance.

A list of indices, decision variables, and parameters used in the model are given below.

- **Indices**

Type of truck/engine	$k \in \{0,1,2,\ldots,K\}$
Set of customer vertices	$i \in \{1,2,\ldots,N\}$

- **Decision Variable**

X_{ijk} $X_{ijk} = 1$ if a vehicle type k traveling from i to j, OW $X_{ijk} = 0$,$\forall\ i, j \in N, k \in K$

Y_{ij} The vehicle load from the customer i to j.

U_{ik} The load of vehicle k after visiting customer i.

τ_i The start time of each customer service.

- ***Parameters***

o_k Operational cost

G_k Vehicle capacity of type k.

q_i Customer's demand.

d_{ij} The distance between customers i and customer j.

L_{ij} The travel time between customers i and customer j where $i \neq j$

H_k The operational range of vehicles of type k.

a_i, b_i The time window for each customer i.

S_i Service time of each customer.

μ Very large number.

M_{tk} Number of available vehicles of type k at time t.

C Annual working days.

- **The objective function and constraints:**

$$(M_{t1}, M_{t2}) = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} o_k \,.\, d_{ij}.X_{ijk} \tag{3.14}$$

Subject to:

$$\sum_{k=1}^{K}\sum_{i=0}^{N} X_{ijk} = 1, \quad \forall j \in \{1,2,\dots,N\} \tag{3.15}$$

$$\sum_{k=1}^{K}\sum_{j=0}^{N} X_{ijk} = 1, \qquad \forall i \in \{1,2,\dots,N\} \tag{3.16}$$

$$\sum_{i=0}^{N} X_{ijk} = \sum_{l=0}^{N} X_{jlk}, \quad \forall j \in \{1,2,\dots,N\},\ \forall k \in \{1,2,\dots,K\} \tag{3.17}$$

$$\sum_{i=0}^{N} Y_{ij} - \sum_{l=0}^{N} Y_{jl} = q_j, \ \forall j \in \{1,2,\dots,N\} \tag{3.18}$$

$$\sum_{i=1}^{N} Y_{i0} = 0 \tag{3.19}$$

$$\sum_{j=1}^{N} Y_{0j} = \sum_{i=1}^{N} q_i \tag{3.20}$$

$$Y_{ij} \le \sum_{k=1}^{K} G_k . X_{ijk}, \ \forall i,j \in \{1,2,\dots,N\}, i \ne j \tag{3.21}$$

$$\sum_{i=1}^{N} X_{i0k} \le M_{kt}, \qquad \forall k \ \in \{1,2,\dots,K\} \tag{3.22}$$

$$\sum_{j=1}^{N} X_{0jk} \le M_{kt}, \qquad \forall k \ \in \{1,2,\dots,K\} \tag{3.23}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ijk} . d_{ij} \le H_k, \quad \forall k \ \in \{1,2,\dots,K\} \tag{3.24}$$

$$U_{ik} + q_i . X_{ijk} - G_k\left(1 - X_{ijk}\right) \leq U_{jk}, \quad \forall i, j \in \{1,2, \dots, N\}, i \neq j, k \in \{1,2, \dots, K\} \tag{3.25}$$

$$q_i \leq U_{ik} \leq G_k, \qquad \forall i \in \{1,2, \dots, N\}, \forall k \in \{1,2, \dots, K\} \tag{3.26}$$

$$\tau_i + S_i + L_{ij} - \mu\left(1 - X_{ijk}\right) \leq \tau_j, \quad \forall i, j \in \{1,2, \dots, N\}, i \neq j, \forall k \in \{1,2, \dots, K\} \tag{3.27}$$

$$a_i \leq \tau_i \leq b_i, \qquad \forall i \in \{1,2, \dots, N\} \tag{3.28}$$

$$Y_{ij} \geq 0, Y_{ii} = 0, X_{ijk} \in \{0,1\} \tag{3.29}$$

The objective of the model is to minimize the operation costs (Equation 3.14). Constraints (3.15, 3.16) ensure that each customer is visited once by one vehicle type. Constraint (3.17) shows that each vehicle entering a customer location must leave that location. Constraint (3.18) guarantees that the difference in demand's value before visiting the customer and after leaving this customer equal to its demand .Constraint (3.19) ensures that all vehicles should return to the depot empty. Constraint (3.20) ensures that the total deliveries leaving the depot are exactly equal to the sum of all customers' demand. Constraint (3.21) implies that the total demand of each vehicle should not exceed its capacity. Constraints (3.22, 3.23) guarantee that the total number of vehicles leave and enter the depot should not exceed the maximum number of available vehicles. Constraint (3.24) limits distance range. Constraints (3.25, 3.26) are for sub-tour elimination. The time window constraints are covered by (3.27, 3.28). Constraint (3.29) refers to the non-negativity of the decision variable and the binary decision variable respectively.

4. COMPUTATIONAL TEST

In this chapter, we present and analyze the mathematical calculations for some of the parameters needed in the models that presented in the previous chapter. In section 4.1 we present the economic calculations for the salvage cost, operation cost, maintenance cost, CO_2 emissions and taxes. In section 4.2, we present two generated instances: one of them the customers were located in a cluster, while the other the customers were randomly distributed. Then after, computational experiments for the proposed methodology are obtained. Lastly, a sensitivity analysis to examine the effect of different values of a vehicle's parameters could change the final output.

4.1 The Economic Calculations

The total vehicle costs can be classified into two main categories; fixed costs and running costs as shown in Figure 4.1. The fixed costs are mainly associated with the costs of ownership, while the operating costs are related to the daily utilization (The travelled distance). Analyzing the vehicle cost clarify that the purchase cost is only a small portion of the total cost of owning a vehicle, which means that even if the electric vehicles have a high purchase cost, it still can be economically feasible.

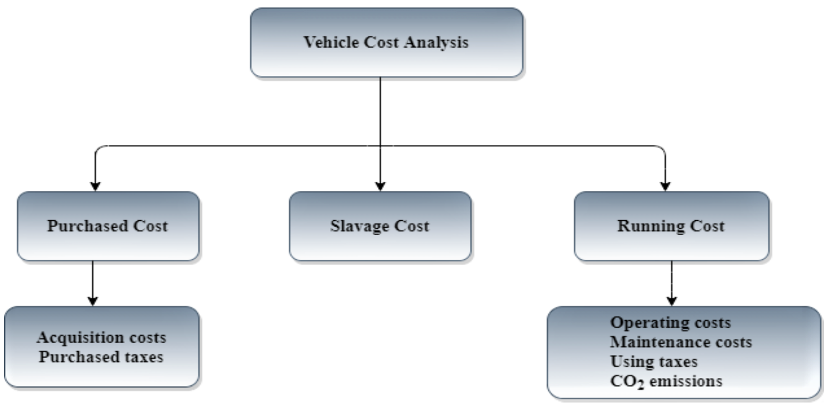


Figure 4.1: Vehicles cost analysis.

In this dissertation, the economic factors such as: purchase cost, salvage value, and operation and maintenance costs are an input in the replacement model, therefore, in this section we will investigate each parameter for both types of vehicles;

conventional and electric. For the purpose of comparison, we used two types of vehicles from the same manufacturer. Table 4.1 shows the vehicle's specifications. The maximum age is assumed to be 10 years for both types of vehicles, also the planning time horizon was assumed to be of 20 years.

Table 4.1: Vehicle's specifications.

Vehicle Types	Conventional vehicles	Electric vehicles
Name	Isuzu NPR truck[1]	Isuzu EV truck[2]
purchasing cost	68000[1]	120000[3]
Operational range	300	174
Body style	Medium	Medium
Maximum age	10	10

4.1.1 Salvage value

The salvage value which is also known as residual value, defined as the potential value obtained by selling vehicles at the end of their useful life. And it depends on the annual depreciation rate of vehicles. The precise estimation of salvage value is an important step, whereas if it's set to be very high, the total income will be overestimated and that will be harmful to the companies, and if it's set to be very low the total income will be underestimated and that will have negative effect on the investments and the future finance of the company. Equation (4.1) is the formula used to calculate the salvage value.

$$FV = PV(1-r)^n \tag{4.1}$$

Where

- FV: The future value.
- PV: The present value.
- r: Annual depreciation rate.
- n: Life time of the asset (years).

The value of the depreciation rate of vehicles varies between 15% and 25% (Feng and Figliozzi 2013). The salvage value for both types of vehicles in our calculation is assumed to be a function of the vehicle's age with 0.2 depreciation rate. Table (4.2)

[1] Market book https://www.marketbook.com.tr/listings/trucks/for-sale/29211795/2019-isuzu-npr-xd
[2] Electric vehicle compare https://evcompare.io/trucks-and-vans/isuzus/isuzu/?from=search.title
[3] Estimated from the US market

shows the salvage value for both types of vehicles over their expected age which is 10 years. In the presented model and as constraints (8 and 9) in section (3.2) indicate, the vehicles must be salvaged at their maximum age, which is in our case 10 years. So the salvage value at age 10 is set to be zero.

Table 4.2: The salvage value for electric and conventional vehicles over the age of vehicles.

Age	Conventional vehicles	Electric vehicles
0	68000	120000
1	55760	98400
2	45723.2	80688
3	37493.02	66164.16
4	30744.28	54254.61
5	25210.31	44488.78
6	20672.45	36480.8
7	16951.41	29914.26
8	13900.16	24529.69
9	11398.13	20114.35

4.1.2 Operating cost

The operating cost refers to the costs that result from the mileage of the vehicles and the fuel consumed. For conventional and electric vehicles the operation costs vary due to the difference in energy prices i.e. electricity and fuel costs. Table (0.3) shows the energy consumption, energy price, annual inflation, CO_2 emissions, and energy taxes, respectively for both types of vehicles.

Table 4.3: The Energy consumptions and costs for both types of vehicles.

Energy Type	Diesel	Electric
Energy consumption	14 mpg[4]	0.75 KWh/mile[3]
Energy Price	$ 3.75 /g[5]	$ 0.096 /KWh[7]
Annual inflation rate	3.29 %[6]	2.2 %[7]
CO_2 emissions	10.18 kg/g[8]	0.641 kg/kwh[9]
Energy taxes	$0.24/gal[9]	0

Several factors affect the operation costs, such as vehicle type, vehicle speed, road surface and gradient (Litman, 2009); Polzin et al, 2008). However, in this thesis

[4] https://www.ttruck.com/toms-truck-center-gas-vs-diesel/
[5] http://www.eia.gov
[6] https://ycharts.com/indicators/us_retail_diesel_price
[7] UsEnergy Information Administration https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_6_a / Table 5.6.A. Average Price of Electricity to Ultimate Customers by End-Use Sector,
[8] https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references
[9] https://afdc.energy.gov/laws/582

those factors are neglected, since they are equivalent for both types of vehicles. Equation (4.2) illustrates the calculation of operation cost depends on energy prices and energy consumption.

$$\text{Operation Cost} = \frac{\text{Energy price}*(1+\text{Inflation rate})^{\text{time}}}{\text{Energy consumption}} \tag{4.2}$$

Using equation (4.2) along with the data from table (4.3) the operation costs for conventional and electric vehicles are calculated as shown in equation (4.3) and equation (4.4) respectively. Where fr, er denote the inflation rate for diesel, and electricity, respectively.

$$O_{ijk=}\frac{\$3.75/gal}{14mpg} \times (1+fr)^j \;\; \forall\, i \in \{0,1,\dots,T\} \;\; \forall j\{0,1,T\} \tag{4.3}$$

$$O_{ijk=}\frac{0.75KWh}{Mile} \times \frac{\$0.096}{KWh}(1+er)^j \;\; \forall\, i \in \{0,1,\dots,T\} \;\; \forall j\{0,1,T\} \tag{4.4}$$

4.1.3 CO2 emissions

In general, the CO_2 emissions in the transport sector come from two main groups: passengers' vehicles and freight transport vehicles. A substantial increase in the CO_2 emissions is expected in the upcoming years due to several factors, such as online shopping, urbanization, and increased numbers of passenger vehicles. A formula from Feng and Figliozzi (2013) has been used along with the information from Table (4.3). The CO_2 emissions are investigated in the life cycle cost analysis, and according to EPA's calculator, the production rate is 10.18 kg/gallon for conventional vehicles and 0.641 kg/Kwh for electric vehicles. Equation (4.5) is the equation to calculate the cost of CO_2 emissions.

$$CO_2 \text{ emissions cost } (e_{fk}) = \frac{co_2 \; emissions\; production\; rate}{energy\; consumption} .\; ec/1000 \tag{4.5}$$

Therefore, equations (4.6, 4.7) illustrate the CO_2 emissions cost calculations for both conventional and electric vehicles:

$$e_{fk} = \frac{10.18\left(\frac{kg}{gal}\right)}{14mpg} . \frac{ec}{1000} \forall i \in \{0,1,\dots,A_K - 1\} \tag{4.6}$$

$$e_{fk} = 0.641 \frac{kg}{kWh} . 0.8 \frac{kWh}{mile} . \frac{ec}{1000} \forall i \in \{0,1, \ldots, A_K - 1\} \quad (4.7)$$

Where the CO_2 emissions cost (ec) reported to be \$ 32.04/t according to the European Union Emissions Trading System (2020). Therefore, the CO_2 emissions cost for electric vehicles is equal to (0.014847), while the CO_2 emissions costs for conventional vehicles is equal to (0.018556). It's worth mentioning that the CO_2 emissions costs are assumed to be constant over the age of the vehicles.

4.1.4 The maintenance and repair costs

To calculate the maintenance cost, a truck maintenance cost calculator was used Freight metrics driving knowledge (2020), where the wheels- tires, engine repair, bearings and seals costs were all considered. The annual estimated maintenance cost equals \$0.1978 per mile for conventional vehicles. It has been reported in Feng and Figliozzi (2013) that the maintenance costs of electric vehicles are 50% less expensive than conventional vehicles. Hence, the following equations were used to estimate the maintenance costs for conventional and electric vehicles, respectively.

$$m_{f1} = (0.1978 + 0.04 \times f) \ \forall \ t\{0,1, \ldots, A_k - 1\} \quad (4.8)$$

$$m_{f2} = (0.0989 + 0.02 \times f) \ \forall \ t\{0,1, \ldots, A_k - 1\} \quad (4.9)$$

Hence, the maintenance costs for both vehicle types is presented in Table (4.4), it is obvious from the table that as the age increases the maintenance costs also increase for both electric and conventional vehicles.

Table 4.4: The maintenance costs for electric and conventional vehicles over the age of vehicles.

Age	Conventional vehicles	Electric vehicles
1	0.24	0.12
2	0.24	0.12
3	0.28	0.14
4	0.32	0.16
5	0.36	0.18
6	0.4	0.2
7	0.44	0.22
8	0.48	0.24
9	0.52	0.26

4.1.5 Energy taxes

The energy tax prices for conventional vehicles were collected from the Alternative Fuels Data Center U.S department of energy (2020) which is equal to \$0.02/gallon. Since the electric vehicles use electricity, the energy taxes prices are set to zero over the age of vehicles. The energy prices are set to be constant over the age of vehicles.

It is worth mentioning that the other taxes related to vehicles are considered as a part of the initial purchase cost. In addition, some costs have been neglected since they are equal for both types of vehicles such as road taxes, parking and penalty costs.

4.1.6 Discount Rate

According to Shogren (2013) the discount rate can be defined as the decrease rate of the discount factor. It is mainly used to obtain the net present value to discount the future cash flow. Equation (4.10) used in order to calculate the value of discount rate

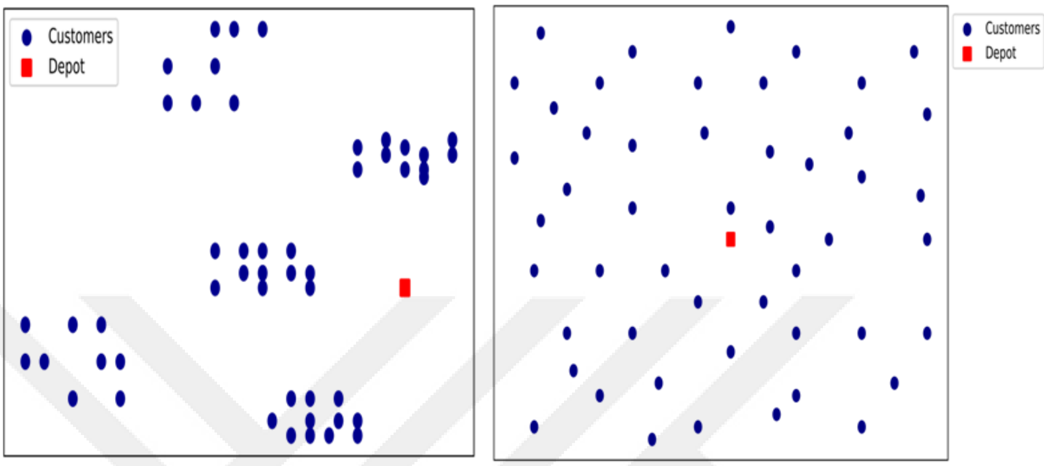
$$dr = \frac{1+\rho}{1+l} \tag{4.10}$$

Where the ρ presented the price index of transportation industry, and l referred to the primary lending rate. The annual discount rate is assumed to be 6% throughout the planning time period.

4.2 Results and Discussion

In this section, we describe the computational results of the proposed methodology. The experiment was executed on GAMS on a standard personal computer, Intel core i3 CPU at 2.1 GHz and 12 GB RAM with Windows 10. Our instances are designed based on (Solomon 1987), where 56 Euclidean instances were created, the instances were categorized according to the geographical distribution of the customer locations, whether they are clustered C, randomly distributed R or randomly clustered RC. In our case, we designed the experiment based on the C and R problems with 50 clustered and random distributed customers respectively, as shown in Figure 4.2.

We generated different fleet compositions each of them consists of 5 vehicles but with different fleet compositions of electric and conventional vehicles and used them in MVRPTW to obtain the minimum operation costs for each one of these fleet compositions. Table 4.5 presents an overview of the results of the MVRPTW for different instances (C, R). The number of the customers, the scenarios, the number of vehicles of each fleet, the values of the objective function, and the distances for each instance for both C and R, respectively. By the definition of the model, all customer demands must be satisfied.



C problem R problem

Figure 4.2: A graphical representation of C and R problems.

Table 4.5: Results of MVRPTW model for different fleet compositions.

C						R					
No. of customers	Scenarios	E	C	Operation cost	Distance	No. of customers	Scenarios	E	C	Operation cost	Distance
50	1	5	0	30.9	401	50	1	6	0	54.89	886.6
50	2	4	1	36.535	393	50	2	5	1	74.367	830.4
						50	3	4	2	98.529	824.05
50	3	3	2	47.784	385	50	4	3	2	84.338	810
50	4	2	3	66.198	371.8	50	5	2	3	126.144	726
50	5	1	4	83.641	369	50	6	1	4	131.394	718
50	6	0	5	95.6	363.5	50	7	0	5	181.249	688.2

The values of the objective function obtained are different for each fleet composition. As the number of electric vehicles increases in the fleet, the objective function decreases, and the reason behind that is that the energy price of electricity is way lower than that of the fuel for each mile. It is worth mentioning that the electric vehicles were able to satisfy the customers demand for this medium size instance in C despite the limited operation range of EV. In the generation of the instances, the minimum number of vehicles needed was determined using trial and error. In instance R, two fleet compositions were unable to satisfy customers demand (fleet of pure 5 EVs and fleet of 4 EVs -1 CVs); the solutions were infeasible due to the limited driving range of electric vehicles or time window violation. In such cases, the number of vehicles in the fleet is increased till a feasible solution is achieved. As a result, a total of 6 vehicles were required for scenarios 1-3, while a total of 5 vehicles were sufficient for the others. Note that we used the results of C instance for the remaining analysis, where the annual operation costs for this instance are fed back into the replacement model along with the initial fleet composition, economic factors, vehicle characteristics, annual budget, and demand to obtain the best replacement policy for a set of mixed fleet vehicles.

Figure 4.3 illustrates the fleet compositions over the planning time horizon of each type of vehicle in each year. The electric vehicles started to appear in the fleet gradually in the first quarter of the time horizon, and thereafter. The majority of vehicles in the fleets over the time horizon are electric vehicles.

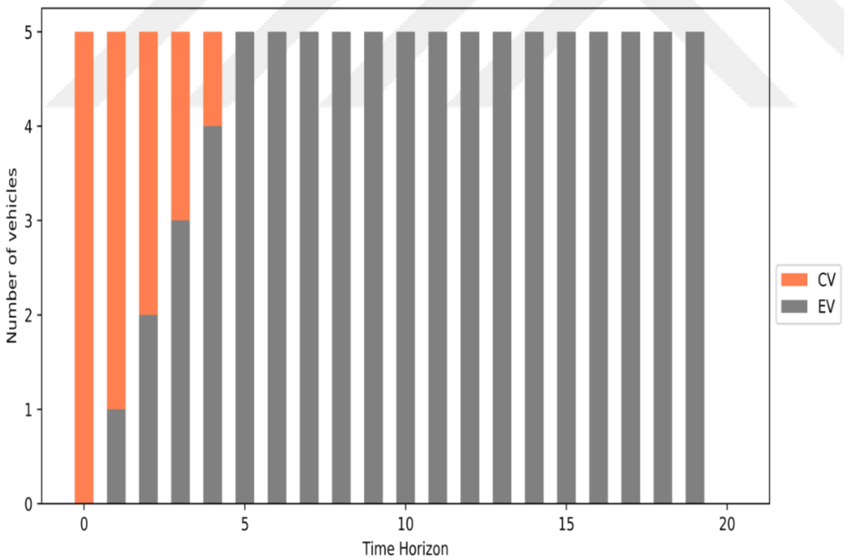


Figure 4.3: The fleet compositions over the planning time horizon of each type of vehicle in each year.

4.2.1 Competitive analysis

In order to assess the performance of our method, we solved the problem using (Feng and Figliozzi 2013) model where the operation cost in their model has a constant value that depends on the vehicle's age. Both formulations aim to optimize the replacement planning strategy for a heterogeneous fleet over a specific time horizon.

According to (Feng and Figliozzi, 2013), the medium and high utilization (over 16000 mile per vehicle) increases the competitiveness of electric vehicles and increases its presence in a fleet composed of electric and conventional vehicles but with a lower rate when battery replacement is included. Therefore, we compare the two models using the same utilization value (18000 mile) over the same time horizon. It is worth mentioning that the vehicle's specifications used in this comparison are based on the previously mentioned in section (4.1) and the battery replacement takes place in year 6.

Table (4.6) shows the results we obtained from comparing the two models under two circumstances: with and without battery replacement. The first and second columns show the results of Feng and Figliozzi (2013) model with and without battery replacement respectively. The third and fourth columns display the results of our model when we do not count the battery replacement and when we count respectively. We also introduce the average number of vehicles from both types that have been used over the entire planning time horizon in the last line.

Table 4.6: Computational results of (Feng and Figliozzi, 2013) model and our proposed model.

Number of vehicles	(Feng and Figliozzi 2013) model				Our proposed model			
	Without battery replacement		With battery replacement		Without battery replacement		With battery replacement	
	EV	CV	EV	CV	EV	CV	EV	CV
Initial number of vehicles	0	5	0	5	0	5	0	5
Average number of used vehicles	3.2 (64%)	1.8 (36%)	0 (0%)	5 (100%)	4.47 (89.4%)	0.53 (10.5%)	4.47 (89.4%)	0.53 (10.5%)

Even though our results indicate no changes in the percentage of the used vehicles with and without battery replacement, the purchasing- salvaging structure has changed, where the model suggests salvaging the electric vehicles rather than replacing the battery. More precisely, the model tends to salvage the electric vehicles at their maximum age when the battery replacement is excluded. Unlike when the battery replacement is included, where the model replaces the electric vehicles at age 6, which is the age of battery. Overall, we deduce that using the proposed integrated model to calculate the optimal number of electric vehicles in the fleet may increase the adoption of electric vehicles in fleets for the same vehicle specifications and same utilization. We also expect that the presence of electric vehicles in the fleet will increase as the time horizon and the battery age increase. Those results emphasize the importance of effective planning of electric vehicles operations.

4.2.2 Sensitivity analysis

Sensitivity analysis was conducted to examine how changes in some vehicle's parameters could change the final output. Battery replacement and CO_2 emissions costs are among the most important variables, which have a large impact on the replacement policy.

Replacement of electric vehicles battery has a large impact on the occurrence of electric vehicles in replacement decision policy in a fleet composed of electric and conventional vehicles. In this section, we performed experiments where the battery replacement cost is considered as a part of the maintenance and repair costs. Charging strategies can improve or deteriorate the lifetime of the battery. Redondo-iglesias et al. (2019) stated that with an optimizing recharge, the battery lifetime greatly increases. According to the authors, the state of charge (the available energy in the battery to the total battery capacity) plays a significant role in deciding the battery lifetime .i.e. as the maximum state of charge decreases, the battery lifetime increases for every battery size. For a 60kWh battery, the battery lifetime is almost 2000, 2500, 3100, and 3800 days with maximum state of charge for 100%, 90%, 80%, and 70% respectively. Therefore, four different scenarios were designed to analyze the effect of battery lifetime on the replacement policy. BloombergNEF forecast battery costs falling under US$100/kWh in 2024 (Keen, 2020). As a worst case scenario, the prices of CO_2 emissions in this section were set to be zero. The results in Figure 4.4 show the percentage of vehicles purchased of both types of vehicles over the planning time horizon for each scenario.

As the results indicate, for scenario 100% and when the lifetime of the battery was around five years, the number of electric vehicles decreased significantly. However, when the charging strategy of scenario 90%, 80%, 70% were obtained, the number of purchased EVs increased over the planning time horizon since the battery lifetime increased. Therefore, the percentage of purchased electric vehicles increases, as the maximum state of charge becomes lower.

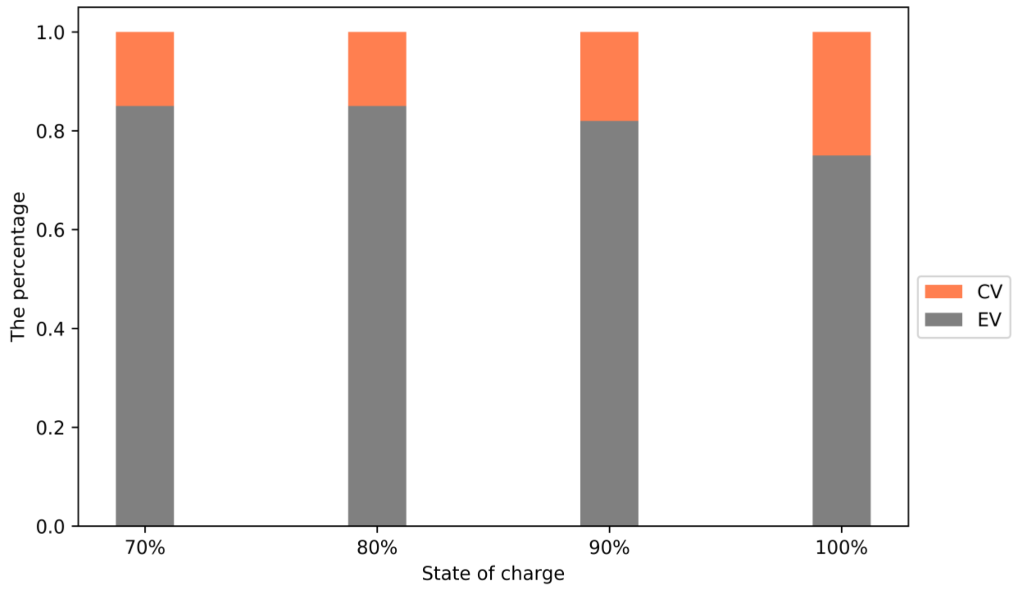


Figure 4.4: The percentage of purchased vehicles for both types for different states of charge over the planning time horizon.

We also investigated the impact of CO_2 emissions cost on optimizing the replacement decision. Therefore, we conducted an experiment by setting CO_2 emissions cost to zero as shown in Table 4.7. Compared to the results we obtained in Table 4.6, it can be concluded that, as expected, as the costs of CO_2 emissions decrease, the average number of electric vehicles also decreases. It is worth mentioning that no change is observed for Feng's model.

Table 4.7: Computational results of the proposed model with CO_2 cost equal to zero.

Type of vehicles	Without battery replacement		With battery replacement	
	EV	CV	EV	CV
Initial number of vehicles	0	5	0	5
Average number of used vehicles	4.16 (85.2%)	0.84 (14.8%)	3.5 (70%)	1.5 (30%)

5. CASE STUDY

This chapter provides an insight into how effective management of electric vehicles in freight operations can or cannot be successfully shifted to real life situations. Therefore, we evaluate the performance of the proposed methodology on a real life delivery operation from a leading retail company inside Istanbul-Turkey.

5.1 Background

Istanbul is the largest city with respect to the population in Turkey, located in north-western (Heper et al, 2018), and can be considered as administrative centres. The total area of Istanbul is 5,343 square kilometers, as of 30.12.2020 (Figure 5.1). The city inhabitants are almost around 15.46 million as of December 31, 2020 (TurkStat, 2021). Recently, the city witnessed new ground and underground projects that enhanced the performance of the urban freight transport system, and helped in evolving this sector to include more services resulting in a positive impact on the country's economy. According to the Turkish Statistical Institute (TurkStat, 2021), the number of vehicles registered in Istanbul are more than 21% of the total vehicles registered in Turkey. The majority of those vehicles are powered by fuel such as Gasoline, and diesel. Such a high level of fuel consumption results in a massive increase in the level of greenhouse gas emissions and imposes negative impacts on the environment.

The transportation activities are increasing inside cities, and Istanbul is not an exception. The conventional vehicles still continue to drive the urban freight operations in Turkey with a heavy dependence on light commercial trucks. According to IEA (2021), 98% of the transportation sector in Turkey is still reliant on oil. In the last decade, there has been a growth in using renewable energy (solar, wind and geothermal) in power generation in different sectors driven by government incentives and projects.

Figure 5.1: Map of Istanbul municipality. (Google map, 2021).

The fuel prices in Turkey are high compared to electricity, where according to (IEA 2021) the fuel prices in Turkey as of 2-9-2021 is equal to $3.48/gallon, compared to $0.097/kw for electricity. In order to increase the reliant in renewable energy, the Turkish government offers a feed-in tariffs (Policy mechanism to increase the use of renewable energy to produce electricity, providing a long term contracts and a specific payments for producers whether they are a households or business for using renewable energy (Nuran Erkul (2020); Wikipedia contributors (2021); Couture and Gagnon (2010)), which may lead to a further decrease in electricity prices in the near future. Despite these potentials, the use of electric vehicles in urban freight in Turkey is is still lagging behind due to the absence of charging stations, where the number of public recharging points in Turkey 1235 units for normal power charge (<=22KW) and 118 units of fast power charge (>22KW) in 2020, most of them implemented in big cities (EAFO 2021). In addition, the absence of clear charging fee policy and the inhomogeneous distribution of electric vehicles charging infrastructure are among the factors that hinder the electrification of urban freight in Turkey (Gonül et al. 2021). Also, the adoption of electric vehicles in freight transport faces a conflict of authorities between different departments including public and private sectors (İmre et al, 2021). Another reason behind the lagging of using electric vehicles in Turkey, is that the government and the inhabitants are unaware of the negative impact of greenhouse gas emissions on the environment (Gonul et al, 2021).

5.2 Description and Modelling Approach

The case study clarifies how the presented methodology can be used to study the adoption rate of electric vehicles in urban freight operation. As mentioned before, the presented case study is from a leading retail company inside Istanbul-Turkey, where customers served directly from a single depot that is located in the inner city of Istanbul. Figure 5.2 shows the customers locations.

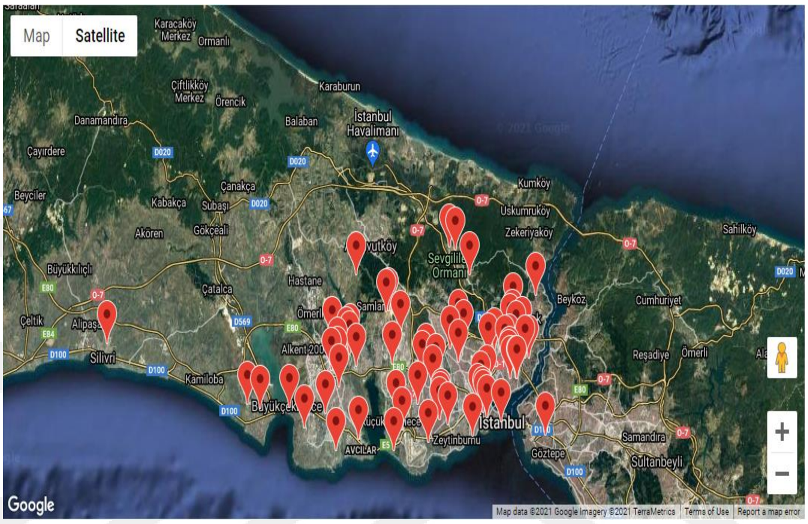


Figure 5.2: Customer’s locations.

The problem consists of 75 customers each of which has a demand which does not exceed the vehicles capacity. The vehicle’s routes start and end at the depot, and each customer is visited once. The deliveries have to start and end within a specific time (time window). We considered a planning time horizon of 20 years. The purchase costs and fuel costs for both types of vehicles from the Turkey market are as presented in Table (5.1). It can be noted that the energy prices in Turkey are close to the U.S market. The purchase costs for the two vehicles are $120000 and $68000 for electric and conventional vehicles, respectively, including all the other related costs. However, recently Turkey increased the taxes on electric vehicles. Therefore, we studied the replacement decision from two different perspectives, with and without subsidies. Where subsidies means the prices before the taxes increased. For the size of electric vehicle we used, the purchase cost increased by 10% (Reuters, 2021).

Service time is set to be equal for all the customers by all vehicles. The customer demands are based on historical data where the demand for each customer is below the vehicle’s capacity for both types of vehicles, the customers were prioritized based on their time window. The retail company is now operating with a fleet of pure conventional vehicles, therefore, the initial fleet composition in this section is assumed to be all new conventional vehicles.

Table 5.1: The purchase costs and Energy prices for both types of vehicles in Turkey the market.

	Electric vehicles	Conventional vehicles
Purchase cost with subsidies	120000[10]	68000[11]
Purchase cost without subsidies	132000	68000
Fuel cost	\$0.097/kw [12]	\$3.422/gal[13]
Energy consumption	1.33 mile/ KWh [14]	14 mpg [15]
CO2 emissions penalty cost	0	0
Planning time horizon (years)	20	20
Vehicle’s age	10	10

We started by calculating the operation costs for all fleet compositions using the fleet size and mixed vehicle routing model with time window as illustrated in Table 5.2. The table indicates the number of customers, the number of scenarios, the fleet compositions, operation costs, annual operation costs, and the distances, respectively. The number of vehicles needed to satisfy the customer’s demand was 6 vehicles.

Table 5.2: Results of MVRPTW model for different fleet compositions.

NO. of customers	Scenarios	EVs	CVs	Operation costs	Annual operation costs	Distance
75	1	6	0	44.235	11058.75	574.415
75	2	5	1	56.314	14078.5	557.539
75	3	4	2	67.331	16832.75	534.9
75	4	3	3	74.794	18698.5	510.12
75	5	2	4	86.115	21528.75	481.592
75	6	1	5	102.75	25687.5	468.12
75	7	0	6	113.736	28434	432.456

10 Estimated from the U.S market
11 Market book https://www.marketbook.com.tr/listings/trucks/for-sale/29211795/2019-isuzu-npr-xd
12 Global petrol prices: https://www.globalpetrolprices.com/Turkey/
13 Global petrol prices: https://www.globalpetrolprices.com/Turkey/
14 http://www.eia.gov
15 https://www.ttruck.com/toms-truck-center-gas-vs-diesel/

Six electric vehicles were able to satisfy the customer's demand, since the maximum distance between the customers was 49.881 mile, which is way below the maximum range of vehicles (174 mile). Figure (5.3) and Figure (5.4) show the fleet composition for both electric and conventional vehicles over the specific planning time horizon, when the CO_2 emissions cost (ec) is set to zero, and $28/ton, respectively, since the prices of CO_2 emissions in Turkey are not specified yet (more detailed elaboration in the sensitivity analysis section). The following equation used to calculate the CO_2 emissions cost rate (e_{fk})for electric and conventional vehicles:

$$CO_2 \text{ emissions cost } (e_{fk}) = \frac{\text{co}_2 \text{ emissions production rate}}{\text{energy consumption}} .\ ec/1000 \tag{5.1}$$

It is obvious that the number of electric vehicles in the fleet composed of electric and conventional vehicles increases as the CO_2 emissions cost increases.

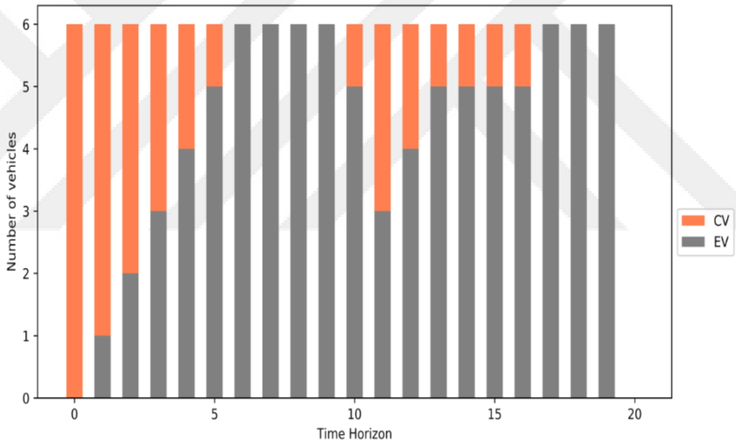


Figure 5.3: Fleet composition for both types of vehicles over the planning time horizon when CO_2 emissions cost equal zero.

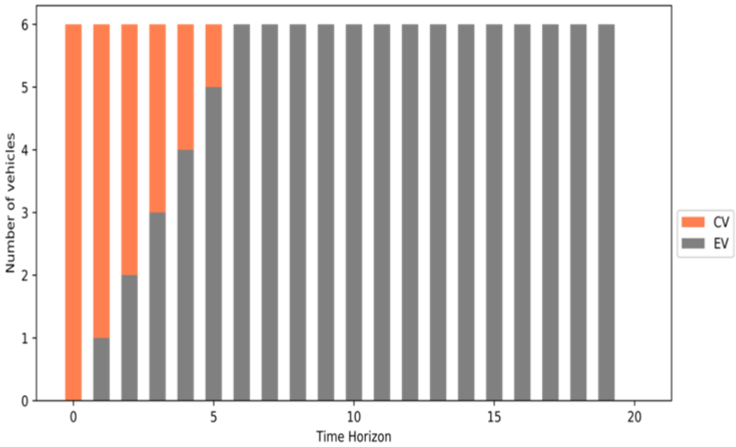


Figure 5.4: Fleet composition for both types of vehicles over the planning time horizon when CO_2 emissions cost equal $28/ton.

5.3 Sensitivity Analysis

To illustrate how the number of used vehicles from both types is affected by the change of some parameters, we performed many scenarios with different settings.

- **CO_2 emissions costs**

In recent decades, environmental awareness has been growing due to climate change and the depletion of natural resources. Different countries around the world set ambitious targets for reducing greenhouse gas emissions and pollution such as the United States, China and the European union. According to the Statistical Review of World Energy (2021) the CO_2 emissions produced in Turkey in 2020 was 369.5 million ton compared to 276.3 million ton in 2010. Figure (5.5) shows the CO_2 emissions per capita in Turkey in 2019 which is around 5.01 tons/cap.

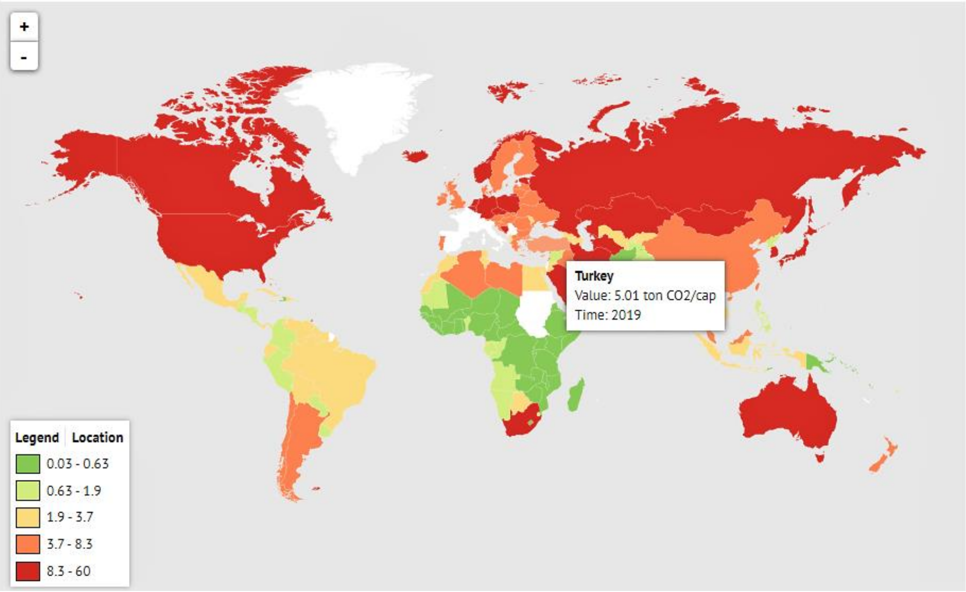


Figure 5.5: The CO2 emissions produced in Turkey per capita. (URL-1.)

Transport is the source of 13% of greenhouse gas emissions in Turkey, most of which are due to road transport as shown in Figure (5.6). Despite its major contributor, the transportation sector witnessed small environmental improvements in last decade due to many reasons such as increasing the number of used vehicles, both for passengers and goods, where the the total number of vehicles used in Turkey in 2019 was around 23 million vehicles with almost 38% growth from 2009 (TurkStat, 2021).

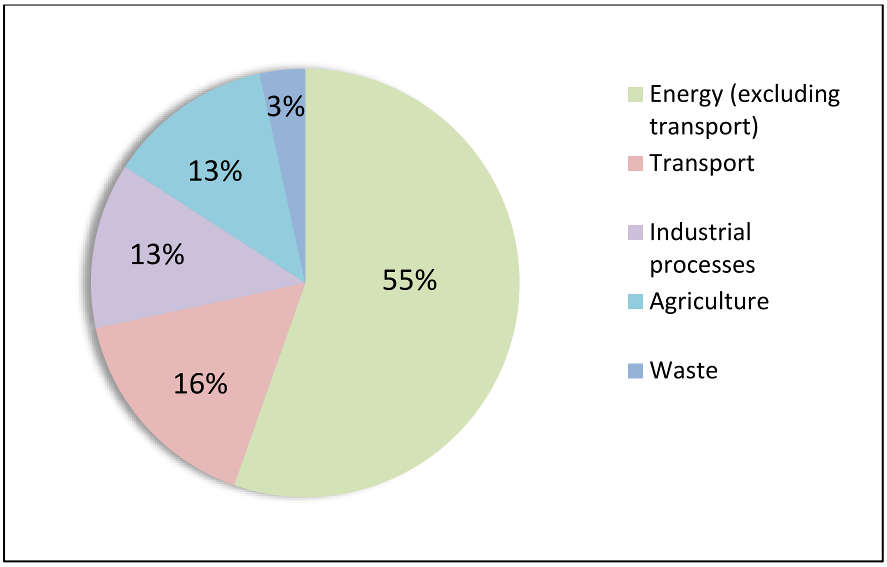


Figure 5.6: The Overall GHG emissions by sector in Turkey (ICAP, 2021).

According to (ICAP, 2021) the CO_2 emissions costs in Turkey are unclear, where on February 17, 2021, the Minister for Environment and Urbanization announced the implementation of a national ETS (Emissions Trading Systems) but a possible start date was not announced. Therefore a sensitivity analysis is conducted to investigate the effect of different CO_2 emissions costs on the purchasing decision for a fleet composed of electric and conventional vehicles in Turkey.

We present four different scenarios each of which has different CO_2 emissions costs. As Table 5.3 and Figure 5.7 show, the results are sensitive to the prices of CO_2 emissions, if the prices of CO_2 emissions decrease the number of electric vehicles in the fleet decreases. When the CO_2 emissions prices were $28/t the percentage of electric vehicles was around 86% of the total vehicles in the fleet with the subsidies and around 79% without subsidies. While the percentage decreased to around 57% when the prices of CO_2 emissions were set to zero including subsidies, and around 43% without subsidies.

Table 5.3: The percentage of used vehicles from both types for different CO_2 emissions costs.

CO_2 emission costs	$28/ ton		$21/ ton		$15/ton		Zero	
	EV	CV	EV	CV	EV	CV	EV	CV
Without subsidies	79%	21%	69%	35%	63%	39%	57%	43%
With subsidies	86%	14%	81%	19%	77%	23%	74%	26%

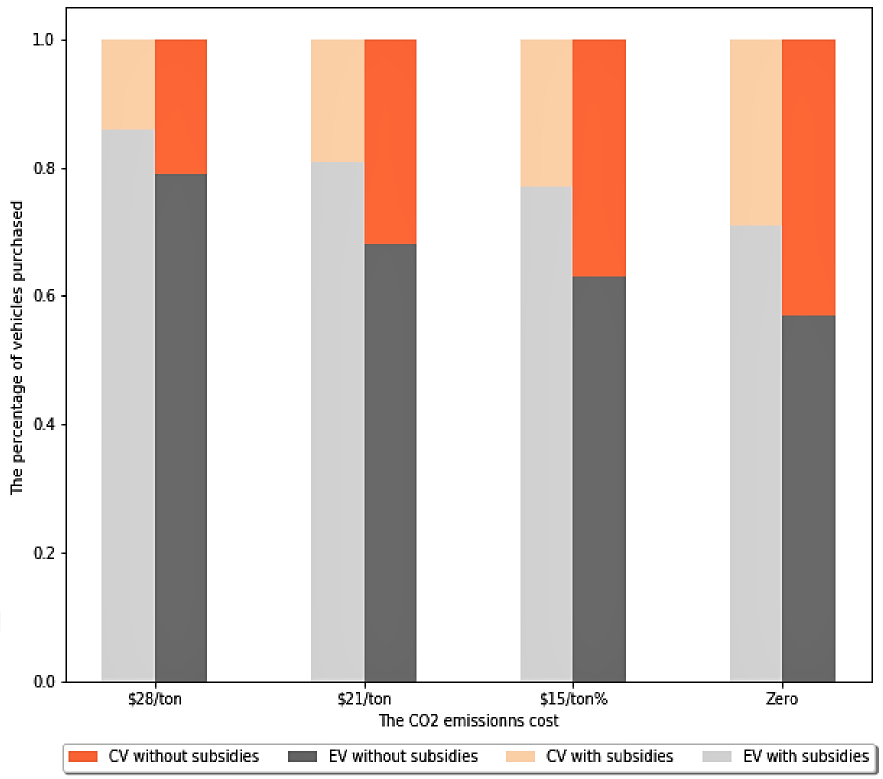


Figure 5.7: The number of used vehicles from both types for different CO_2 emissions prices.

- **Maintenance costs**

According to Feng and Figliozzi (2012) the maintenance cost is one of the most difficult cost functions that can be estimated. There are many reasons behind this; first, electric vehicles are still a new technology where there is a shortage in maintenance workshops that can deal with electric vehicles technology in many countries. Also, the prices of vehicle components vary from one country to another, beside the lack of data for old vehicles maintenance costs. Therefore, we presented two scenarios to study the replacement decision for electric and conventional vehicles considering two maintenance costs, the first one with 25% increase, and the second with 25% decrease over the age of vehicle. It is worth mentioning that the electric vehicles maintenance cost is 50% less expensive than conventional vehicles (Feng and Figliozzi, 2013). As the results in Table 5.4 and Figure 5.8 show, the presence of electric vehicles in the fleet increased as the maintenance costs increased, whereas, when the prices decreased, the number of used conventional vehicles increased.

Table 5.4: The percentage of used vehicles from both types for different maintenance costs.

Maintenance costs	25% Higher		Original case		25% lower	
	Without subsides	With subsides	Without subsides	With subsides	Without subsides	With subsides
EV	75%	79%	57%	74%	45%	67%
CV	25%	22%	43%	26%	55%	33%

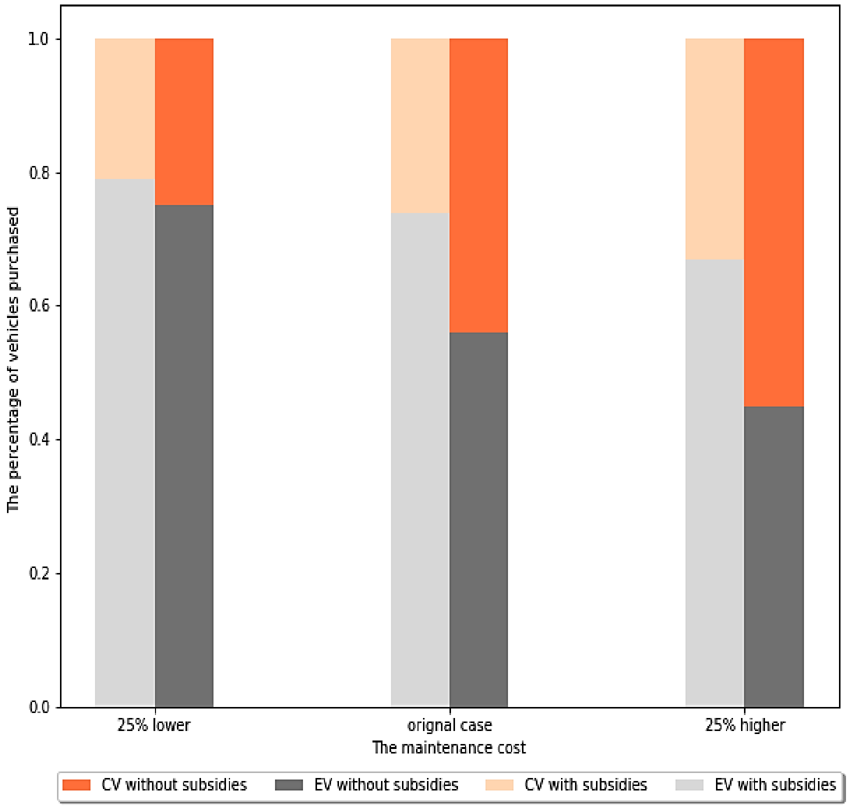


Figure 5.8: The number of used vehicles from both types for different maintenance costs.

- **Depreciation rate**

The depreciation rate can be defined as the decline in the value of used vehicles over their age. According to some researchers the uncertainty related to the depreciation rate for electric vehicles is higher than that of conventional vehicles, others argued that in the upcoming years the conventional vehicles will have a higher depreciation rate subject to many limitations such as zero emission zones, and inner-city access restrictions (Franckx, 2019). Due to this conflict and the lack of precise information we assumed that both types of vehicles will depreciate at the same rate. More precisely, we used one of the most frequent methods in depreciation called the straight line method shown in Figure 5.9, where the value of vehicles depreciated at a constant rate of the initial value for both types of vehicles (Sahu et al. 2017).

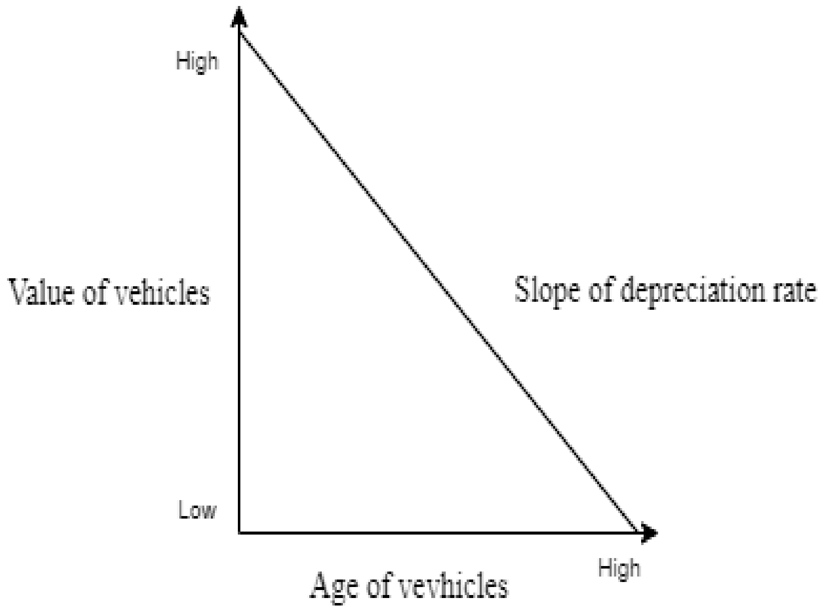


Figure 5.9: Illustration of straight line method for depreciation rate.

In order to investigate the impact of depreciation rate on the fleet composition decisions, three different scenarios from two different perspectives (with and without subsidies) were generated, each of them have a different depreciation rate (18%, 21%, 25%) as shown in Table 5.5 and Figure 5.10. As the depreciation rate increases, the number of electric vehicles in the fleet decreases, and the reason behind that, is the high initial cost of electric vehicles compared to conventional ones. So when the value depreciates fast, the competitiveness of electric vehicles decreases.

Table 5.5: The percentage of used vehicles from both types for different depreciation rates.

Depreciation rate	18%		21%		25%	
	Without subsides	With subsides	Without subsides	With subsides	Without subsides	With subsides
EV	57%	74%	49%	51%	36%	38%
CV	43%	26%	51%	49%	63%	62%

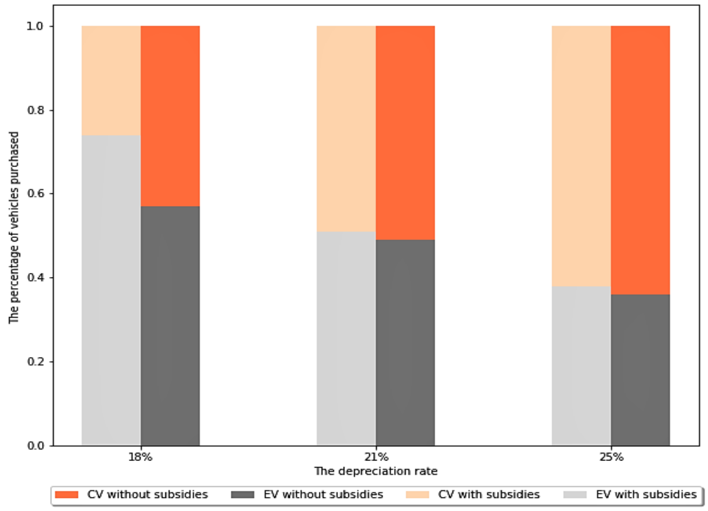


Figure 5.10: The percentage of used vehicles from both types for different depreciation rate values.

- **Breakeven analysis**

A breakeven analysis is also performed for different purchase costs scenarios, from two different perspectives; with and without subsidies as illustrated in Figure 5.11. With subsidies case scenario, when the purchase cost is set to be higher than the market prices by 42.5% the fleet becomes all conventional, while without subsidies, the purchase cost must increase by almost 30% to reach a fleet composed of only conventional vehicles. It is clear that, as the purchase cost of electric vehicles increases, their competitiveness decreases. Therefore, the government subsidies are an essential factor to move toward the electrification of urban freight in Turkey, and increasing the adoption rate of electric vehicles.

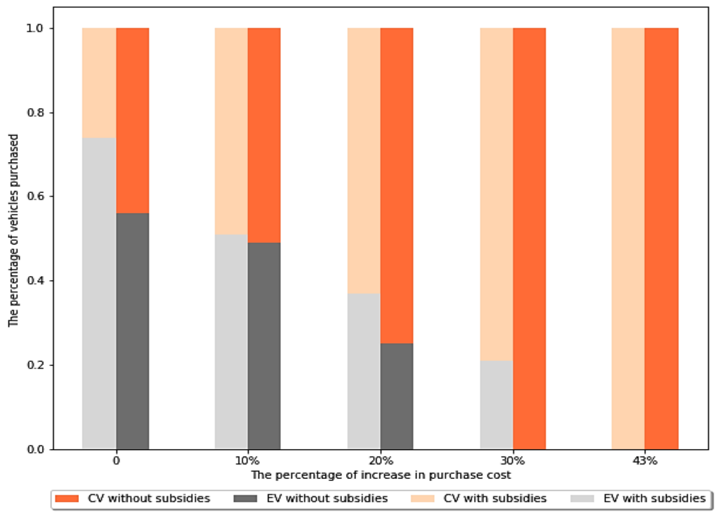


Figure 5.11: The percentage of vehicles used over the planning time horizon for different purchasing costs with and without subsidies.

Table 5.6 shows the computational results of Feng and Figliozzi (2013) model and our proposed model for the average number of used vehicles when the CO_2 emissions cost were either \$28/ton or zero.

Table 5.6: Computational results of (Feng and Figliozzi,2013) model and our proposed for the average number of used vehicles without subsidies.

Average Number of used vehicles	Feng and Figliozzi (2013)		Our proposed model	
	EV	CV	EV	CV
CO_2 =\$28/ton	66%	34%	79%	21%
CO_2 = 0	34%	66%	57%	43%

- **Potential implications**

Various governments and logistics companies are confronting continuous challenges to present sustainable solutions to overcome the environmental deterioration, and the shortage in energy sources. In this section, we introduce potential implications for both researchers and policy makers from the results we obtained, and the scenario analysis we performed in the previous sections.

- One of the main aspects in supply chain management is to design an effective distribution network with a reasonable transportation cost. Although many companies are dedicated to reduce their greenhouse gas emission, they also emphasized the need for long-term cost effective perspective when investing in new vehicles instead of conventional ones. The proposed model shows a practical implication for decreasing the total cost over the planning time horizon compared to (Feng and Figliozzi, 2013) model. To show that, we used a future replacement policy from (Feng and Figliozzi, 2013) model, where the model was conducted using the same parameter values and vehicle specifications that were used in the presented case study and with the same objective function. After running the model, we noted the age and year for each vehicle purchased/ salvaged from both types of vehicles over the planning time horizon, in addition to the total cost. Then, the results were executed in our model to compare the total cost for both models when the same replacement policy is carried out. In order to do that, constraints were added to our proposed model to specify the number of purchased/salvaged in each year. After comparing the results we obtained from executing (Feng and Figliozzi, 2013) replacement policy in our model and the results of (Feng and Figliozzi, 2013) model, the results show that our model was able to reduce the total cost by 8.38% compared to (Feng and Figliozzi, 2013) model over the entire planning horizon when executing the same replacement policy.

- The presented model could be seen as a preliminary attempt to evaluate the actions of logistic companies when applying different policies and the effectiveness of those policies in deploying electric vehicles in urban freight operations through combining optimization model and economic analysis. For logistics companies the upfront cost is one of the main reasons that limit the adoption rate of electric vehicles. The results show that government subsidies have a direct impact on the purchase decisions, so that when the subsidies were counted, the number of electric vehicles was purchased over the planning time horizon increased. The sensitivity analysis also showed that the CO2 emissions and the depreciation rate can largely affect the company's purchase decisions.

6. CONCLUSION

In this thesis, we developed an integrated model that takes into consideration replacement and routing decisions to manage a fleet composed of electric and conventional vehicles in urban freight operations. In this final chapter, we will provide a summary for each chapter, a conclusion that is derived from the results. The chapter also includes a limitations section followed by future work.

6.1 Summary

This section summarize the different

- Chapter 1: explained the scope and the purpose of the problem, In addition to the main contributions.
- Chapter 2: start with a general introduction of the fleet management in urban freight transport and the strategies used, followed by the key factors affecting the process of electrifying the urban freight and a SWOT analysis. A state of art of the literatures for both fleet size and mixed vehicle routing problem and replacement model are given.
- Chapter 3: The construction of the proposed methodology is given. First, we presented the mathematical formulation of the replacement model. Then the mathematical formulation of fleet size and mixed vehicle routing problem with time window is given.
- Chapter 4: The economic calculations for some of the parameters needed in the models are calculated. The results are also presented along with performance analysis and sensitivity analysis.
- Chapter 5: A case study from a real life situation in the city of Istanbul is presented, experiments results show that the methodology can be applied on real life data.

6.2 Conclusion

To address the problem of managing a fleet composed of electric and conventional vehicles in urban freight, we developed a novel methodology that handles both routing and replacement decisions. This integration allows us to design a complete model that takes into consideration most of real-life parameters. More precisely, we have introduced an integrated mixed vehicle routing problem with a time window and fleet replacement model for managing a fleet of electric and conventional vehicles for urban freight operations. In this problem, a routing plan has to be made for all possible fleet compositions of the initial fleet using the fleet size and mixed vehicle routing problem with time a window with an objective function to minimize the operation cost. Thereafter, the results are feedback into the replacement model along with other economic factors and vehicle specifications to find the optimal replacement policy.

Results from the computational experiments show that efficient planning of electric vehicle usage in urban operations can increase their presence compared to conventional vehicles. This is an important insight, since it shows that the adoption rate of electric vehicles in urban freight fleets may increase with better planning techniques, related to electric vehicles or with the increased experience of operational managers with electric vehicles, which brings operational effectiveness by trial-and-error.

The method can be used directly for any mixed fleet planning problem. However, given the high computational complexity of the method, as the size of the problem increases in terms of number of customers, finding an exact solution will be burdensome. Moreover, the vehicle routing model will need modifications if the vehicles are allowed to return to the depot for recharging. Further studies are also required for generalization of the results to see the potential impact of optimizing EVs adoption rate. Different vehicle characteristics and GHGs emissions costs can be considered. Also due to the significant technological advancement in the electric vehicles industry and constant change in fuel prices, the current results will have to be updated in the future.

The results of the sensitivity analysis show that, to obtain more electric vehicles in the fleet composition, the battery life time has to increase, and that can be achieved by optimizing the charging strategies. We have observed that in the presence of CO_2 emissions cost and battery replacement options, our integrated model suggests a higher adoption rate of electric vehicles compared to the basic fleet management model. We also presume our suggested model will make a higher difference for problems with a solution close to the break-even point, where the total costs of conventional and electric vehicles are similar. However, more instances should be studied in the future for more reliable results. At the end, it is worth mentioning that the presented model can be applied to diverse real life situations such as bus fleets, garbage collection fleets, pick up delivery fleets, big or small industrial companies.

Another implication from the sensitivity analysis is that there is an obvious need to develop a freight vision in Turkey along with policies and mechanisms to price the CO_2 emissions, which would be an indirect way to promote the use of electric vehicles in urban freight distributions. As long as the prices of CO_2 emissions are not defined precisely, the electric vehicles market growth in Turkey is restrained. From the different sensitivity analysis that has been done, the overall conclusion is that there is an affirmative attitude toward the use of electric vehicles in urban freight operations. On the other hand, policies that help in increasing the use of electric vehicles in urban freight in Turkey are still lagging behind, despite being so efficient. A sensitivity analysis was done for different cases by lowering and increasing the maintenance costs, the number of electric vehicles used over the planning time horizon was unsurprisingly increased when the maintenance cost increased, as the maintenance cost of electric vehicles is lower than that of conventional vehicles, which is a good implication for the Turkish market, since the prices of components for both types of vehicles are expected to increase. Also a sensitivity analysis for the depreciation rate was considered, the results indicate that as the depreciation rate increases the number of electric vehicles decreases. User's acceptance is one of the reasons that lead to a high depreciation rate. Implementing the charging infrastructure in the large cities may increase the user's acceptance and the trust to use the electric vehicles, along with the government's promotion of the positive impact of electric vehicles on the environment can decrease the depreciation rate.

In terms of the quality of the solutions obtained by the proposed methodology, from chapter four and five we can conclude that the methodology is competitive and quite comprehensive as it takes the different operation cost for different composition of fleet composed of electric and conventional vehicles into consideration and along with the other economic factors.

6.3 Limitations

This PhD research concern about the adoption rate of electric vehicles in urban freight operations, while the previous section present the main findings of this research, this section introduce its limitations:

- In this study, we only investigated electric and conventional vehicles, the use of plug-in hybrid electric vehicles that have the characteristics of both conventional vehicles and electric vehicles was not included. Those vehicles have two engines; an internal combustion engine and a pure electric engine and it is easy to switch between the two modes (Hiermann et al. 2019). In this way, the electric mode can be used on specific routes, and the impact of limited operational range of electric vehicles on the routing plans can be diminishing.
- In chapter 2, different strategies for urban freight transport were discussed such as road pricing and urban consolidation centers, however, due to shortage of time, the research was only limited to the alternative vehicles (especifically electric vehicles), the feasibility of other strategies along with electric vehicles was not discussed.
- In chapter 4, the CO_2 emissions costs were calculated as part of the cost analysis, however, the greenhouse gas emissions include other gases: Carbon dioxide, Methane, Nitrous oxide, Chlorofluorocarbons. Those gas costs were not included due to the lack of information.

6.4 Future Work

The transportation in urban freight is an extensive topic which involves many factors, methods, considerations and problems. Recently, using electric vehicles gained increasing attention, but researches in this area is still needed to increase. Even though the developed model in this thesis presents a holistic view to the adoption of electric vehicles in urban freight operations, there remain many avenues to investigate in this arena of future research including the following:

- In future research, it would be valuable to extend the model to cover recharging, where electric vehicles have the ability to fully or partially recharge during the tour, and then analyze the effect of those different charging strategies on the battery lifetime and therefore on the competitiveness of electric vehicles.
- Also from a modeling perspective, it is good to consider the dynamic parameters of the problem such as stochastic travel time and service time. Therefore, the dynamic fleet size and mixed vehicle routing problem should be studied in the future.
- Due to the significant technological advancement in the electric vehicles industry and constant change in fuel prices, the current results will have to be updated in the future.
- In addition, we hope to include the government policies and regulations in our studies and to investigate their impacts on the replacement decision, where these policies include the cost of economic and environmental considerations.
- Also, it will be interesting to apply the presented model to other types of fleets that have different characteristics.

REFERENCES

Adhikari M, Ghimire LP, Kim Y, Aryal, P. and Khadka, S.B. (2020) Identification and analysis of barriers against electric vehicle use. *Sustain 12*:1–20. https://doi.org/ 10.3390/SU12124850

Ahani P, Arantes A, Melo S. (2018) A portfolio approach for optimal fleet replacement toward sustainable urban freight transportation. *Transp Res Part D 48*:357–368. https://doi.org/10.1016/j.trd.2016.08.019

Ajanovic A, Haas R. (2016) Dissemination of electric vehicles in urban areas: Major factors for success. *Energy 115*:1451–1458. https://doi.org/10. 1016/j.energy.2016.05.040

Alizadeh Foroutan R, Rezaeian J, Mahdavi I. (2020) Green vehicle routing and scheduling problem with heterogeneous fleet including reverse logistics in the form of collecting returned goods. *Appl Soft Comput J 94*:106462. https://doi.org/10.1016/j.asoc.2020.106462

Aljohani K, Thompson RG. (2018) *A* stakeholder-based evaluation of the most suitable and sustainable delivery fleet for freight consolidation policies in the inner-city area. S*ustain 11*:.https://doi.org/10.3390/ su11010124

Allen J, Anderson S, Browne M, Jones P. (2000) *A framework for considering policies to encourage sustainable urban freight traffic and goods/service flows. Transp Stud Group*, Univ Westminster, London

Allen J, Thorne G, Browne M. (2007) Good practice guide on urban freight transpor. BESTUFS administration centre NEA Transport research and training

Ambrosini C, Routhier J. (2004) Objectives, methods and results of surveys carried out in the field of urban freight transport: an international comparison. *Transp Rev 24*:57–77

Amirhosseini B, Hosseini SMH. (2018) Scheduling charging of hybrid-electric vehicles according to supply and demand based on particle swarm optimization, imperialist competitive and teaching-learning algorithms. *Sustain cities Soc 43*:339–349

Ashkrof P, Homem de Almeida Correia G, van Arem B. (2020) Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands. *Transp Res Part D Transp Environ 78*:102206. https://doi.org/10.1016/j.trd.2019.102206

Balinski ML, Quandt RE. (1964) On an integer program for a delivery problem. *Oper Res 12*:300–304

Baskak M, Kahraman C. (1998) Fuzzy replacement analysis. *Annu Conf North Am Fuzzy Inf Process Soc - NAFIPS 77*–81. https://doi.org/10.1109/NAFIPS.1998.715535

Baster H, Bentzen K, Bentzen L, Laugesen MS. (2014) Supporting electric vehicles in freight transport in Amsterdam.

Bean JC, Lohmann JR, Smith RL. (1994) Equipment replacement under technological change. *Nav Res Logist 41*:117–128

Behrenbeck K, Thonemann U, Merschmann U. (2007) Soft secrets of supply chain success. *International Commerce Review* 144-150

Behrends S, Lindholm M, Lindholm M, Woxenius J. (2008) The impact of urban freight transport: A definition of sustainability from an actor's perspective. *Transp Plan Technol 31*:693–713

Bethoux O. (2020) *H*ydrogen fuel cell road vehicles and their infrastructure: An option towards an environmentally friendly energy transition. *Energies 13*:. https://doi.org/10.3390/en13226132

Blattberg R, Golanty J. (1978) Tracker: An early test market forecasting and diagnostic model for new product planning. In: Perspectives On Promotion And Database Marketing: The Collected Works of Robert C Blattberg. *World Scientific*, pp 177–187

Bojovic N, Milenkovic M. (2008) The best rail fleet mix problem. *Oper Res 8*:77–87

Bräysy O, Gendreau M. (2005) Vehicle routing problem with time windows, Part I: Route construction and local search algorithms. *Transp Sci 39*:104–118. https://doi.org/10.1287/trsc.1030.0056

Browne M, Allen J. (2011) Enhancıng The Sustaınabılıty Of Urban Freıght Transport And Logıstıcs. *Transp Commun Bull Asia Pacific 44*:1–19

Browne M, Allen J, Leonardi J. (2011) Evaluating the use of an urban consolidation centre and electric vehicles in central London. *IATSS Res 35*:1–6. https://doi.org/10.1016/j.iatssr.2011.06.002

Browne M, Sweet M, Woodburn A, Allen J. (2005) *Urban Freight Consolidation Centres. Transp Sudies Group*, University Westminster

Bunsen T, Cazzola P, D'Amore L, Gorner M, Scheffer S, Schuitmaker R, Signollet H, Tattini J, Paoli JT (2019) Global EV Outlook 2019 to electric mobility. *OECD* https://www.iea.org/reports/global-ev-outlook-2019. 232

Caceres-Cruz J, Arias P, Guimarans D, Riera D, Juan AA. (2014) Rich Vehicle Routing Problem. *ACM Comput Surv 47*:1–28. https://doi.org/10.1145/2666003

Calvete HI, Galé C, Oliveros MJ, Sánchez-Valverde B. (2007) A goal programming approach to vehicle routing problems with soft time windows. *Eur J Oper Res 177*:1720–1733. https://doi.org/10.1016/j.ejor.2005.10.010

Chand S, Sethi S. (1982) Planning Horizon Procedures for Machine Replacement Models With Several Possible Replacement Alternatives. *Nav Res Logist Q 29*:483–493. https://doi.org/10.1002/nav.3800290310

Chang PT. (2005) Fuzzy strategic replacement analysis. *Eur J Oper Res 160*:532–559. https://doi.org/10.1016/j.ejor.2003.07.001

Christofides N, Mingozzi A, Toth P. (1981) Exact algorithms for the vehicle routing problem, based on spanning tree and shortest path relaxations. *Math Program 20*:255–282

Chwesiuk K, Kijewska K. (2010) Urban consolidation centres for medium-size touristic cities in the Westpomeranian Region of Poland. *Procedia Soc Behav Sci 2*:6264–6273. https://doi.org/10.1016/j.sbspro.2010.04.036

Clarke G, Wright JW. (1964) Scheduling of vehicles from a central depot to a number of delivery points. *Oper Res 12*:568–581

Conshohocken P. (2021) IKEA U.S. to convert its New York last mile delivery fleet to electric vehicles. Retreived May 20, 2021 from *https://www.ikea.com/us/en/this-is-ikea/newsroom/ikea-u-s-to-convert-its-new-york-last-mile-delivery-fleet-to-electric-vehicles-by-may-2021-pube101cc30.*

Coren MJ. (2019) Amazon orders 100,000 electric delivery trucks, doubling the fleet in Europe and North America. Retreived May 21, 2021 from *https://qz.com/1712151/amazon-orders-100000-electric-delivery-trucks/.*

Couture T, Gagnon Y. (2010) An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. *Energy Policy 38*:955–965

Dantzig GB, Ramser JH. (1959) The truck dispatching problem. *Manage Sci 6*:80–91

Datz D, do Couto Strongylis CMR, Neto HXR. (2009) Urban Freıght Transportatıon And The Quantıfiable Consequences Of Ineffıcıent Plannıng On Urban Sustaınabılıty. *Hum Settl Dev* III 171

Davis BA, Figliozzi MA. (2013) A methodology to evaluate the competitiveness of electric delivery trucks. *Transp Res Part E Logist Transp Rev 49*:8–23. https://doi.org/10.1016/j.tre.2012.07.003

Delaître L, Routhier JL. (2010) Mixing two French tools for delivery areas scheme decision making. *Procedia - Soc Behav Sci 2*:6274–6285. https://doi.org/10.1016/j.sbspro.2010.04.037

DHL (2021) Streetscooter And The Future Of Electrıc Vehıcles. Retreived May 23, 2021 from https://www.dhl.com/discover/business/ business-ethics/ future-of-electric-vehicles.

Diana M, Pirra M, Woodcock A. (2020) Freight distribution in urban areas: a method to select the most important loading and unloading areas and a survey tool to investigate related demand patterns. E*ur Transp Res Rev 12*:. https://doi.org/10.1186/s12544-020-00430-w

Downing S. (2020) 8 electric truck and van companies to watch in 2020. *Rereived in 30 May 2021 from https://www.greenbiz.com/article/8-electric-truck-and-van-companies-watch-2020.*

Du JY, Brunner JO, Kolisch R. (2016) Obtaining the optimal fleet mix: A case study about towing tractors at airports. *Omega 64*:102–114. https://doi.org/10.1016/j.omega.2015.11.005

EAFO (2021) Charging infra stats. European Alternative Fuels Observatory Retreived January 30, 2021 form *https://www.eafo.eu/alternative-fuels/ electricity/ charging-infra-stats*

Eilon S, Watson-Gandy CDT, Christofides N, de Neufville R. (1974) Distribution Management-Mathematical Modelling And Practical Analysis. *IEEE Trans Syst Man Cybern* 589

Eleonor M, Blinge M. (2014) Assessing knowledge and awareness of the sustainable urban freight transport among Swedish local authority policy planners. *Transp Policy 32*:124–131.https://doi.org/10.1016/ j.tranpol.2014.01.004

Emiliano W, Alvelos F, Telhada J, Lanzer EA. (2020) An optimization model for bus fleet replacement with budgetary and environmental constraints. *Transp Plan Technol 43*:488–502. https://doi.org/10.1080/03081060. 2020.1763656

Etezadi T, Beasley JE. (1983) Vehicle fleet composition. *J Oper Res Soc 34*:87–91

Faure L, Burlat P, Marquès G. (2016) Evaluate the Viability of Urban Consolidation Centre with Regards to Urban Morphology. *Transp Res Procedia 12*:348–356. https://doi.org/10.1016/j.trpro.2016.02.071

Feng W, Figliozzi M. (2013) An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. *Transp Res Part C Emerg Technol 26*:135–145. https://doi.org/10.1016/j.trc.2012.06.007

Feng W, Figliozzi M. (2012) Bus Fleet Type and Age Replacement Optimization: A case study utilizing King County Metro fleet data. *Proc Conf Adv Syst Public Transp 1*–14. https://doi.org/10.3969/j.issn.1672-7126.2011. 01.03

Figliozzi M, Boudart J, Feng W. (2012) Economic and Environmental Optimization of Vehicle Fleets. *Transp Res Rec J Transp Res Board 2252*:1–6. https://doi.org/10.3141/2252-01

Fisher ML, Jaikumar R. (1981) A generalized assignment heuristic for vehicle routing. *Networks 1*1:109–124

Foltyński M. (2014a) Electric Fleets in Urban Logistics. Procedia - *Soc Behav Sci 151*:48–59. https://doi.org/10.1016/j.sbspro.2014.10.007

Foltyński M. (2014b) Electric fleets in urban logistics. *Procedia-Social Behav Sci 151*:48–59

Forde M. (2020) Amazon, DHL, Ikea, others join electric vehicle alliance. Retrieved Febreuary 13, 2021 from *https://www.supplychaindive.com/ news/amazon-dhl-ikea-others-join-electric-vehicle-alliance/570915/.*

Franckx L. (2019) Total cost of ownership of electric cars compared to diesel and gasoline cars in Belgium.

Freight metrics driving knowledge. (2020) Maintenance Costs calculator. Retrieved February 11, 2021 from *https://freightmetrics.com.au/try-it-now/*

Furnari E, Johnnes L, A.Pfeiffer, S.Sahdev. (2020) Why most eTrucks will choose overnight charging. Retreived March 11, 2021 from *https://www.mckinsey.com/industries/automotive -and-assembly/our-insights/why-most-etrucks-will-choose-overnight-charging*

Gillett BE, Miller LR. (1974) A heuristic algorithm for the vehicle-dispatch problem. *Oper Res 22*:340–349

Goeke D, Schneider M. (2015) Routing a mixed fleet of electric and conventional vehicles. *Eur J Oper Res 245*:81–99. https://doi.org/10.1016/j.ejor.2015.01.049

Golden B, Assad A, Levy L, Gheysens F. (1984) The fleet size and mix vehicle routing problem. *Comput Oper Res 11*:49–66

Gonül O, Can Duman, Güler O (2021) Electric vehicles and charging infrastructure in Turkey : An overview. *Renew Sustain Energy Rev 143*:. https://doi.org/10.1016/j.rser.2021.110913

Green EH, Skerlos SJ, Winebrake JJ. (2014) Increasing electric vehicle policy efficiency and effectiveness by reducing mainstream market bias. *Energy Policy 65*:562–566

Gundes S. (2016) The Use of Life Cycle Techniques in the Assessment of. 216:916–922. https://doi.org/10.1016/j.sbspro.2015.12.088

Hall D, Lutsey N. (2020) Electric Vehicle Charging Guide for cities. International Council on Clean Transportation

Hans Quak HJ. (2011) Urban freight transport: The challenge of sustainability. *City Distrib Urban Freight Transp Mult Perspect 37*–55. https://doi.org/10.4337/9780857932754.00008

Hartman JC. (2000) Parallel replacement problem with demand and capital budgeting constraints. *Nav Res Logist 47*:40–56. https://doi.org/10.1002/(SICI)1520-6750(200002)47:1<40::AID-NAV3>3.0.CO;2-T

Hartman JC, Ban J. (2002) The series-parallel replacement problem. *Robot Comput Integr Manuf 18*:215–221. https://doi.org/10.1016/S0736-5845(02)00012-1

Heper M, Öztürk-Tunçel, Criss D, Bilge N. (2018) Historical dictionary of Turkey. Rowman & Littlefield

Hiermann G, Hartl RF, Puchinger J, Vidal T. (2019) Routing a Mix of Conventional , Plug-in Hybrid , and Electric Vehicles To cite this version : *HAL Id* : hal-01668228. 272:235–248

Hoff A, Andersson H, Christiansen M, Hasle G, Løkketangen A. (2010) Industrial aspects and literature survey: Fleet composition and routing. *Comput Oper Res 37*:2041–2061. https://doi.org/10.1016/j.cor.2010.03.015

Holguín-Veras J, Leal J.A, Sánchez-Diaz I, Browne M, Wojtowicz J. (2020) State of the art and practice of urban freight management Part II: Financial approaches, logistics, and demand management. *Transp Res Part A Policy Pract 137*:383–410. https://doi.org/10.1016/j.tra.2018.10.036

Hopp WJ, Nair SK. (1991) Timing replacement decisions under discontinuous technological change. *Nav Res Logist 38*:203–220

ICAP (2021) *Emissions Trading Worldwide: Status Report 2021.*

IEA (2019) Tracking Transport., IEA, Paris https://www.iea.org/reports/tracking-transport-2019

IEA (2021) Energy Prices: Overview. Retreived September 2, 2021 from https://www.iea.org/reports/energy-prices-overview.

İmre Ş, Çelebi D, Koca F. (2021) Understanding barriers and enablers of electric vehicles in urban freight transport: Addressing stakeholder needs in Turkey. *Sustain Cities Soc 68*:102794

Irnich S, Schneider M, Vigo D. (2014) Chapter 9: Four variants of the vehicle routing problem. In: Vehicle Routing: Problems, Methods, and Applications, Second Edition. SIAM, pp 241–271

Islam A, Lownes N. (2019) When to go electric? A parallel bus fleet replacement study. *Transp Res Part D Transp Environ 72*:299–311. https://doi.org/10.1016/j.trd.2019.05.007

Jin D, Kite-Powell HL. (2000) Optimal fleet utilization and replacement. *Transp Res Part E Logist Transp Rev 36*:3–20. https://doi.org/10.1016/S1366-5545(99)00021-6

Juan AA, Mendez CA, Faulin J, De Armas J, Grasman SE. (2016) Electric Vehicles in Logistics and Transportation: A Survey on Emerging Environmental, Strategic, and Operational Challenges. *Energies 9*:86. https://doi.org/10.3390/ en9020086

Karabakal N, Lohmann JR, Bean JC. (1994) *P*arallel Replacement under Capital Rationing Constraints. *Manage Sci 40*:305–319. https://doi.org/ 10.1287/mnsc.40.3.305

Keen K. (2020) As battery costs plummet, lithium-ion innovation hits limits, experts say. https://www.spglobal.com/marketintelligence/en/news-insights/ latest-news-headlines/as-battery-costs-plummet-lithium-ion-innovation-hits-limits-experts-say-58613238

Keles P, Hartman JC. (2004) Case study: Bus fleet replacement. *Eng Econ 49:253–278. https:*//doi.org/10.1080/00137910490498951

Kleindorfer PR, Neboian A, Roset A, Spinler S. (2012) Fleet renewal with electric vehicles at la Poste. Interfaces (Providence) 42:465–477. https://doi. org/10.1287/inte.1120.0640

Laporte G. (1992) The vehicle routing problem: An overview of exact and approximate algorithms. *Eur J Oper Res 59*:345–358

Lebeau, P., De Cauwer, C., Van Mierlo, J., Macharis, C., Verbeke, W. and Coosemans, T (2015) Conventional, Hybrid, or Electric Vehicles: Which Technology for an Urban Distribution Centre? *Sci World J* 2015:. https://doi.org/10.1155/2015/302867

Lebeau P, Macharis C, van Mierlo J, Maes G. (2013) Implementing electric vehicles in urban distribution: A discrete event simulation. *World Electr Veh J 6:*38–47

Lee YH, Kim JI, Kang KH, Kim KH. (2008) A heuristic for vehicle fleet mix problem using tabu search and set partitioning. *J Oper Res Soc 59*:833–841. https://doi.org/10.1057/palgrave.jors.2602421

Li L, Lo HK, Xiao F, Cen X. (2016) Mixed bus fleet management strategy for minimizing overall and emissions external costs. *Transp Res Part D Transp Environ 60*:104–118. https://doi.org/10.1016/j.trd.2016.10.001

Lilley C. (2020) Electric vehicle market statistics. In: Next Green Car. Retreived August, 3 2021from https://www.nextgreencar.com/electric-cars/statistics/.

Litman T. (2009) Transportation cost and benefit analysis. *Victoria Transp Policy Inst 31*:1–19

Macharis C, Lebeau P, Van Mierlo J, Lebeau K. (2013) Electric versus conventional vehicles for logistics: A total cost of ownership. *World Electr Veh J 6*:945–954. https://doi.org/10.3390/wevj6040945

Macrina G, Di Puglia Pugliese L, Guerriero F, Laporte G. (2019) The green mixed fleet vehicle routing problem with partial battery recharging and time windows. *Comput Oper Res 101*:183–199. https://doi.org/10.1016/j.cor.2018.07.012

Macrina G, Laporte G, Guerriero F, Di Puglia Pugliese L. (2019) An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows. *Eur J Oper Res 276*:971–982. https://doi.org/10.1016/j.ejor.2019.01.067

Mahajan V, Yoram W. (1985) Innovation Diffusion Models of New Product Acceptance : A Reexamination

Manoharan Y, Hosseini SE, Butler B, Alzhahrani H, Senior BT, Ashuri T, Krohn J. (2019) Hydrogen fuel cell vehicles; Current status and future prospect. *Appl Sci 9*:. https://doi.org/ 10.3390/app9112296

Mathew T V, Khasnabis S, Mishra S. (2010) Optimal resource allocation among transit agencies for fleet management. *Transp Res Part A Policy Pract 44*:418–432

Mirhedayatian SM, Yan S. (2018) *A* framework to evaluate policy options for supporting electric vehicles in urban freight transport. *Transp Res Part D 58*:22–38. https://doi.org/10.1016/j.trd.2017.11.007

Montreuil B, Rougès J-F, Cimon Y, Poulin D. (2012) The physical internet and business model innovation. *Technol Innov Manag Rev 2*: 1927-0321

Mouhrim, N, Alaoui AEH, Boukachour J. (2018) Vehicle routing problem with mixed fleet of electric and conventional vehicles under emissions allowances. *4th International Conference on Logistics Operations Management (GOL). IEEE,*

Nallusamy N, Sakthivel P, Chausalkar A, Ramadhas AS. (2016) Electric vehicles. Altern Fuels. *Transp* 295–320

Nuran Erkul. (2020) Tariff scheme key for investors in Turkey's renewables. Retreived August 28, 2021 from https://www.aa.com.tr/en/energy/finance/tariff-scheme-key-for-investors-in-turkey-s-renewables/28511

Oakford R V, Lohmann J r, Salazar A. (1984) A dynamic replacement economy decision model. *IIE Trans 16*:65–72

Oakford R V, Lohmann JR, Salazar A. (1981) A dynamic equipment replacement model. In: *IIE Spring Annual Conference Proceedings*. pp 103–108

Parthanadee P, Buddhakulsomsiri J, Charnsethikul P. (2012) A study of replacement rules for a parallel fleet replacement problem based on user preference utilization pattern and alternative fuel considerations. *Comput Ind Eng 63*:46–57. https://doi.org/10.1016/j.cie.2012.01.011

Polzin SE, Chu X, Raman VS. (2008) Exploration of a shift in household transportation spending from vehicles to public transportation. *No. NCTR* 576-02. 2008

Potvin J-Y, Rousseau J-M. (1993) A parallel route building algorithm for the vehicle routing and scheduling problem with time windows. *Eur J Oper Res 66*:331–340

Pringle LG, Wilson RD, Brody EI. (1982) NEWS: A decision-oriented model for new product analysis and forecasting. *Mark Sci 1*:1–29

Quak H, Nesterova N, Rooijen T Van, Dong Y. (2016) Zero emission city logistics : current practices in freight electromobility and feasibility in the near future. *Transp Res Procedia 14*:1506–1515. https://doi.org/10.1016/j.trpro.2016.05.115

Quigley E V. (2019) *Five Deep Decarbonization Strategies.* Retrieved in 23 June 2021from https://www.cleanenergytransition.org/post/five-deep-decarbonization-strategies.

Rahimi K, Davoudi M. (2018) Electric vehicles for improving resilience of distribution systems. *Sustain Cities Soc 36*:246–256. https://doi.org/10.1016/j.scs.2017.10.006

Redondo-Iglesias E, Vinot E, Venet P, Pelissier S. (2019) Electric vehicle range and battery lifetime: a trade-off. In: *EVS32*. p 9p

Reid C. (2019) And, Breathe: London To Get U.K.'s First Zero-Emission Street. Retrieved May 20, 2021 from https://www.forbes.com/sites/carltonreid/2019/12/16/and-breathe-london-to-get-uks-first-zero-emission-street/?sh=785be65502d4.

Research and Market (2020) *Global Electric Vehicle Supply Equipment (ESVE) Market 2020-2025 by Type, Application and Region*

Reuters (2021) Turkey raises special consumption tax on electric vehicles to 10-60%. Retrieved August 18, 2021 from https://www.reuters.com/article/turkey-tax-motor-int-idUSKBN 2A20DR.

Rezgui D, Aggoune-Mtalaa W, Bouziri H. (2015) Towards the electrification of urban freight delivery using modular vehicles. *10th IEEE Int Conf Serv Oper Logist Informatics, SOLI 2015* - conjunction with ICT4ALL 2015 154–159. https://doi.org/10.1109/SOLI.2015.7367611

Rezgui D, Chaouachi Siala J, Aggoune-Mtalaa W, Bouziri H. (2019) Application of a variable neighborhood search algorithm to a fleet size and mix vehicle routing problem with electric modular vehicles. *Comput Ind Eng 130*:537–550. https://doi.org/10.1016/j.cie.2019.03.001

Rogic K, BRANI SLA V S, GO RAN K. (2007) Methodology of introducing fleet management system. *Promet-Traffic&Transportation 20*:105–111

Rouse M. (2017) Fleet Management. Retreived July 23, 2020 from https://whatis.techtarget.com/definition/fleet-management.

Ruesch M. (2004) Road pricing and urban freight transport: Practices and developments from the BESTUFS project. *WIT Trans Built Environ 75*:895–904

Rushmeier RA, Kontogiorgis SA. (1997) Advances in the optimization of airline fleet assignment. *Transp Sci 31*:159–169

Russo F, Comi A (2012b) City Characteristics And Urban Goods Movements: A Way To Environmental Transportation System İn A Sustainable City. *Procedia-Social Behav Sci 39*:61–73

Sahu AK, Narang HK, Sahu AK, Sahu NK. (2017) Machine Economic Life Estimation Based On Depreciation-Replacement Model. *Cogent Eng 2*:. https://doi.org/10.1080/23311916.2016.1249225

Salhi S, Wassan N, Hajarat M. (2013) The fleet size and mix vehicle routing problem with backhauls: Formulation and set partitioning-based heuristics. T*ransp Res Part E Logist Transp Rev 56*:22–35

Sanguesa JA, Torres-Sanz V, Garrido P, Martinez FJ, Marquez-Barja JM. (2021) A Review on Electric Vehicles: Technologies and Challenges. *Smart Cities 4*:372–404. https://doi.org/10.3390/smartcities4010022

Sassi O, Cherif WR, Oulamara A. (2015) Vehicle Routing Problem with Mixed fleet of conventional and heterogenous electric vehicles and time dependent charging costs. *Int J Math Comput Phys Electr Comput Eng 9:*167–177

Schiffer M, Klein PS, Laporte G, Walther G. (2021) Integrated planning for electric commercial vehicle fleets : A case study for retail mid-haul logistics networks. *Eur J Oper Res 291*:944–960. https://doi.org/10.1016/j.ejor.2020.09.054

Scriven R. (2019) Global Battery Electric Truck Market to Grow 20 % in 2019. Retreived January 13, 2021 from https://www.interactanalysis.com/battery-electric-truck-market-to-grow-20-in-2019-despite-dip-in-2018

Shogren J. (2013) *Encyclopedia of energy, natural resource, and environmental economics.* Newnes

Silk AJ, Urban GL. (1978) Pre-test-market evaluation of new packaged goods: A model and measurement methodology. *J Mark Res 15*:171–191

Socio M De. (2021) Keep your eyes on these 9 electric truck and van companies in 2021. Retrieved May 30, 2021 from https://www.greenbiz.com/ article/keep-your-eyes-these-9-electric-truck-and-van-companies-2021.

Solomon MM. (1987) Algorithms for the vehicle routing and scheduling problems with time window constraints. *Oper Res 35*:254–265

Song Z, Liu Y, Gao H, Li S. (2020) The underlying reasons behind the development of public electric buses in China: The Beijing case. *Sustain 12*:1–16. https://doi.org/10.3390/su12020688

Statistical Review of World Energy (2021) *Statistical Review of World Energy.* London

Stefanelli T, Di Bartolo C, Galli G, Pastori E, Quak H. (2015) Making urban freight logistics more sustainable. *Civ Policy Note* 1–63

Taefi TT, Kreutzfeldt J, Held T, Konings R, Kotter R, Lilley S, Baster H, Green N, Laugesen MS, Jacobsson S, Borgqvist M. (2016) Comparative analysis of european examples of freight electric vehicles schemes—a systematic case study approach with examples from denmark, germany, the netherlands, sweden and the uk. In: Dynamics in logistics. *Springer*, pp 495–504

Taefi TT, Kreutzfeldt J, Held T, Fink A. (2016) Supporting the adoption of electric vehicles in urban road freight transport – A multi-criteria analysis of policy measures in Germany. *Transp Res Part A 91*:61–79. https://doi.org/10.1016/j.tra.2016.06.003

Teoh T, Kunze O, Teo CC, Wong YD. (2018) Decarbonisation of urban freight transport using electric vehicles and opportunity charging. *Sustain 10*:. https://doi.org/10.3390/su10093258

Transport Decarbonization Alliance. (2020) Zero-Emissions Zones. Retreived March 15, 2021 from https://c40.my.salesforce.com/sfc/ p/#36000001 Enhz/a/1Q000000gRoY/yXvLet8UAkS_r0.7MHty3eMyVN.fAcwX5 wAwerJDN.k

TurkStat (2021), Turkish Statistical Institute, 2020, Rerived in July 20, 2021 from https://biruni.tuik.gov.tr/bolgeselistatistik/degiskenle-rUzerindenSorgula.do?durum=acKapa&menuNo=108&altMenuGoster=1&secilenDegiskenListesi=UCL

URL-1<Energyconsumption data from BP Statistical Review of World Energy: https://www.bp.com/en/global/corporate/energy-economics/ statistical-review-of-world-energy.html> Data retrieved. 7 .8.2021

Van Duin JHR, Muñuzuri J. (2015) Urban distribution centers. *City Logist Mapping the Futur* 115–134

Van Duin JHR, Tavasszy LA, Quak HJ. (2013) Towards E(lectric)-urban freight: First promising steps in the electric vehicle revolution. *Eur Transp - Trasp Eur* 1–19

Vander Veen DJ, Jordan WC. (1989) Analyzing trade-offs between machine investment and utilization. *Manage Sci 35*:1215–1226

Wappelhorst S, Hall D, Nicholas M, Lutsey N. (2020) Analyzing Policies To Grow the Electric Vehicle Market in European Cities

Williams WW, Fowler OS. (1980) Minimum Cost Fleet Sizing for a University Motor Pool. *Interfaces (Providence) 10*:21–29. https://doi.org/10.1287/inte.10.3.21

Wu H, Alberts G, Hooper J. (2017) New market. New entrants. New challenges. Battery Electric Vehicles. *Deloitte*

Żak J, Redmer A, Sawicki P. (2011) Multiple objective optimization of the fleet sizing problem for road freight transportation. *J Adv Transp 45*:321–347

Zhao M, Lu Y. (2019) A heuristic approach for a real-world electric vehicle routing problem. *Algorithms 12*:1–19. https://doi.org/10.3390/a12020045

Ziarati K, Soumis F, Desrosiers J, Solomon MM. (1999) A branch-first, cut-second approach for locomotive assignment. *Manage Sci 45*:1156–1168

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- **Al-dalain, R**., & Celebi, D**.** 2021. Planning a Mixed Fleet of Electric and Conventional Vehicles for Urban Freight with Routing and Replacement Considerations. *Sustainable Cities and Society*, 103105.