



**TÜRKİYE CUMHURİYETİ
ADANA ALPARSLAN TÜRKER SCIENCE AND TECHNOLOGY
UNIVERSITY**

**GRADUATE SCHOOL
INDUSTRIAL ENGINEERING DEPARTMENT**

**AN INTEGRATED SIMULATION-OPTIMIZATION MODEL AND
MULTI-CRITERIA DECISION-MAKING MODEL FOR
DETERMINING OF E-VEHICLE FLEET**

BÜŞRA TÜMAY

M.Sc.



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**THESIS ADVISOR
ASSOC. PROF. DR. CANSU DAĞSUYU**

ADANA, 2024

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

17/07/2024

[Signature]

Büşra TÜMAY

ÖZET

E-ARAÇ FİLOSUNUN BELİRLENMESİ İÇİN ENTEGRE BİR SİMÜLASYON- OPTİMİZASYON MODELİ VE ÇOK KRİTERLİ KARAR VERME MODELİ

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Yüksek Lisans, Endüstri Mühendisliği Anabilim Dalı

Danışman: Doç. Dr. Cansu DAĞSUYU

Temmuz 2024, 97 sayfa

Teknoloji ve dijitalleşme büyük bir hızla gelişmektedir. Günümüzde birçok ürüne çok hızlı erişim sağlanabilmektedir. Ürün satın almak için mobil uygulama kullanımının artması, sipariş sayısında artışa yol açacak, bu da siparişlerin firmadan müşteriye ulaştırılmasını içeren taşıma sisteminde yoğunluğu arttıracaktır. Son mil taşımacılığındaki bu yoğunluk, fosil yakıtların yanmasından kaynaklanan zararlı gazların salınımını da artıracaktır. Firmaların çevreye verdikleri zararı azaltabilmeleri için alternatif yeşil araçları ulaşım sistemlerine entegre etmeleri gerekmektedir.

Bu çalışmada, simülasyon-optimizasyon modeli kullanılarak şirketlerin elektrikli araçlara geçişi sırasında CO₂ emisyonu ve teslimat maliyeti minimizasyonu hedeflerini karşılayacak araç filoları belirlenmiştir. Çalışma kapsamında üç farklı drone kapasitesi, e-motosiklet ve klasik motor incelenmiş ve beş farklı araç modu için 7 farklı senaryo geliştirilmiştir. Yatırım maliyetlerini de dikkate alarak en uygun senaryonun belirlenmesinde TOPSIS yaklaşımı kullanılmıştır. Orta kapasitedeki drone ve e-motorsiklet kullanımı en yüksek önceliğe sahip senaryo olarak belirlenmiştir.

Anahtar Kelimeler: son kilometre taşımacılığı, TOPSIS, simülasyon, optimizasyon

ABSTRACT

AN INTEGRATED SIMULATION-OPTIMIZATION MODEL AND MULTI-CRITERIA DECISION-MAKING MODEL FOR DETERMINING OF E-VEHICLE FLEET

Büşra TÜMAY

M.Sc., Department of Industrial Engineering

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July 2024, 97 pages

The advancement of technology and digitalization is progressing rapidly. Nowadays, many products can be readily accessed with great speed. The use of mobile applications has increased, leading to a rise in the number of orders, which in turn will increase the density of vehicles used in the last phase of the transportation system that involves the delivery of orders from the company to the customer. This intensity in last-mile will also increase the emission of harmful gases from the combustion of fossil fuels. Companies need to integrate alternative green vehicles into their transportation systems in order to reduce environmental damage without falling behind in the competition.

In this study, the vehicle fleets that will meet the companies' CO₂ emission and delivery cost minimization targets as they transition to electric vehicles were identified using the simulation-optimization model. The study focused on analyzing three different drone capacities, as well as e-motorcycles and classic motorcycle. Additionally, seven scenarios were developed to evaluate five various vehicle modes. TOPSIS approach was used to determine the most suitable scenario, taking into account CO₂ emission, delivery cost and investment costs. The use of medium-capacity drones and e-motorcycles has been determined as the highest priority scenario.

Keywords: last mile transportation, TOPSIS, simulation, optimization

Dedication

Für die Familie.

Für meine Vergangenheit, Gegenwart und Zukunft.

ACKNOWLEDGEMENTS

I would like to thank my dear advisor, Assoc. Prof. Dr. Cansu DAĞSUYU, for all her kindness, intimacy, guidance, support, and sharing her valuable information and suggestions with me from the beginning to the end of my thesis. Also I would like to show my gratitude for approaching me with the understanding and warmth of a friend.

For their valuable constructive criticism, I stay humble before the dear members of the thesis committee, Prof. Dr. Tolunay Göçken, and Prof. Dr. Ali Kokangül. Their objective feedback helped me take this study to a much more efficient level allowing me to establish a reference point for future studies.

I would like to thank my mother Gülhis TÜMAY, my father Mehmet TÜMAY, my sister Kübra TÜMAY ATEŞ for their emotional support, kind attitude, and understanding towards me during this process even from miles away. Also I would like to show my gratitude for laughing with me and crying with me, for showing me the insignificance of distance when I feel like giving up.

I would like to thank my cat Ares for his emotional support with his mischief and love, and for always be beside me.

Büşra TÜMAY

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LIST OF ABBREVIATIONS

E-commerce	: Electronic commerce
E-grocery	: Electronic grocery
E-fulfillment center	: Electronic fulfillment center
B2C	: Business-to-Consumer
OFD	: Online Food Delivery
FMCG	: Fast-moving Consumer Good
RSS	: Ride-sharing service
PR	: Personalized Ride
ICEV	: Internal Combustion Engine Vehicle
ICE	: Internal Combustion Engine
ICV	: Internal Combustion Vehicle
SOI	: Sustainability Oriented Innovation
GT	: Green Transportation
UAV	: Unmanned Aerial Vehicle
UAS	: Unmanned Aircraft System
SADR	: Sidewalk Autonomous Delivery Robot
RADR	: Road Autonomous Delivery Robot
ADR	: Autonomous Delivery Robot
SUGV	: Small Unmanned Ground Vehicle
AV	: Autonomous Vehicles
CAV	: Connected and Automated Vehicle
EV	: Electric Vehicle
BEV	: Battery Electric Vehicle
HEV	: Hybrid Electric Vehicle
LEV	: Light Electric Vehicle
MHV	: Mild Hybrid Vehicle
HHV	: Heavy Hybrid Electric Vehicle
E-vehicle	: Electric Vehicle
E-motorcycle	: Electric Motorcycle

E-car	: Electric Car
E-truck	: Electric Truck
E-scooter	: Electric Scooter
E-CB	: Electric Cargo Bike
Pro-E-Bike	: Professional Electric Bike
LPG	: Liquefied Petroleum Gas
CNG	: Compressed Natural Gas
GHG	: Green House Gas
CO ₂	: Carbon dioxide
CH ₄	: Methane
N ₂ O	: Nitrous dioxide
SO ₂	: Sulfur dioxide
NO ₂	: Nitrogen dioxide
PM	: Particulate Matter
GWP	: Global Warming Potential
ODP	: Ozone Layer Depletion Potential
POCP	: Photochemical Ozone Creation Potential
FAETP	: Freshwater Aquatic Ecotoxicity Potential
ADP	: Abiotic Depletion Potential
HTTP	: Human Toxicity Potential
COPD	: Chronic Obstructive Pulmonary Disease
VRP	: Vehicle Routing Problem
ERDDP	: Energy Minimizing and Range Constrained Drone Delivery Problem
GVRSP	: Green Vehicle Routing Problem
VRPTW	: Vehicle Routing Problem with Time Windows
MC-VRPTW-D	: Multi-Compartment Vehicle Routing Problem with Time Windows and Drones
FSMVRPTW-EV	: Fleet Size and Mix Vehicle Routing Problem with Time Windows for Electric Vehicles
ALNS	: Adaptive Large Neighborhood Search
MCDM	: Multi Criteria Decision Making
TOPSIS	: Technique for Order Preference by Similarity to Ideal Solution
AHP	: Analytic Hierarchy Process

ABM	: Agent-based Modeling
M&S	: Modeling and Simulation
DES	: Discrete Event Simulation
SC	: State Charts
LCA	: Life Cycle Assessment
LCIA	: Life Cycle Impact Assessment
LCC	: Life Cycle Cost
TCO	: Total Cost of Ownership
DC	: Last delivery point
RT	: Route Type
PD	: Pure-play Drone-based
VMt	: Vehicle-miles traveled
FU	: Functional Unit
FTHR	: First Time Hit Rate
WtT	: Well-to-Tank
TtW	: Tank-to-Wheel
WtW	: Well-to-Wheel
CtL	: Coal-to-Liquid
S	: Sustainability
P	: Policy
O	: Optimization and Scheduling
MCI	: Motivated Consumer Innovativeness
GADD	: Ground Autonomous Delivery Device
A/C	: Air conditioning
GPS	: Global Positioning System
CSS	: Coast Clutch Solenoid
UCC	: Uniform Commercial Code
3D	: Three-dimensional
UK	: United Kingdom
US	: United States
ICTT	: International Council on Clean Transportation
IEA	: International Energy Agency
HEI	: Health Effects Institute

ELP	: European Logistics Provider
BOTAS	: Boru Hatları İle Petrol Taşıma Anonim Şirketi
EUAS	: Elektrik Üretim Anonim Şirketi
TEIAS	: Türkiye Elektrik İletim Anonim Şirketi
MENR	: Ministry of Energy and Natural Resources
EMRA	: Energy Market Regulatory Authority
DHL	: Dalsey, Hillblom ve Lynn
AIMSUN Networks	: Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks
GAMS	: General Algebraic Modeling System
DRU	: Domino's Robotic Unit
B-17	: Boeing 17
CEO	: Chief Executive Officer
COVID-19	: New Coronavirus
TL	: Turkish Lira
EUR	: Euro
min	: minute
h	: hour
km	: kilometer
g	: gram
kg	: kilogram
km/h	: kilometres per hour
km ²	: per square kilometer
Mph	: Miles per hour
KWh	: Kilowatt-hour
CO ₂ e	: CO ₂ equelevent
Gt	: Gross tonnage
CPS	: Cost per shipment
CPP	: Cost per payload unit
etc.	: et cetera
i.e.	: id est

LIST OF SYMBOLS

A^+	: Positive Ideal Solution
A^-	: Negative Ideal Solution
S_i^+ solution	: Difference between each competitive option and the positive ideal
S_i^- solution	: Difference between each competitive option and the negative ideal

1. INTRODUCTION

In recent times, technology has become an always-progressing concept. The rapid development of technology has played a pivotal role in the emergence of digitalization, which encompasses the incorporation of digital tools and systems into every aspect of company operations, ranging from customer service and manufacturing to management and communication [1].

Owing to the rapid developments of digitalization and technology that challenge the imagination, people are able to access a wide range of products, including information, entertainment, education, food, etc. Because these developments have taken customer expectations and behavior in a completely different direction, industries have to adopt this digitalization to thrive in current conditions. Also, customers' purchase decisions are shifting from physical stores to online platforms. For instance, according to worldwide data, 59% of Japanese people, 73% of individuals in the UK, 46% of Chinese people, 65% of individuals in the US, 70% of people in Germany, and 49% of people in Turkey are purchasing online [2].

E-commerce, or the act of trading over the internet with a relationship between a vendor and a buyer, is one of the emerging sectors to keep up with how customers behave. Since it is conducted through digital tools such as smartphones and computers, e-commerce enables customers to access products anytime and anywhere and provides 24/7 shopping opportunities. It may additionally prevent customers from having difficulty making decisions since it provides access to the product contents, prices from various sellers, etc. with ease. Customers' propensity to switch from physical stores to online shopping has also been influenced by these advantages. Another accelerating advantages in the spread of e-commerce is the COVID-19 pandemic. During the pandemic, there has been a significant transition from in-person to online activity across nearly every human activity [3]. Since people cannot go to physical markets, restaurants, etc. like they used to, the necessity for technological solutions for customers has intensified. Due to the threat of the spread of the virus, consumers' buying habits have changed and the request for delivery without contact has increased significantly. An investigation on consumer behavior found that, across all participating countries, at least 25% of consumers said they had permanently changed their behaviors and did not anticipate returning to their pre-pandemic behavior [4]. The changes brought about by the pandemic have been lasting for many customers

and companies. For the convenience of customers, numerous mobile applications (apps) have been made available that cover a wide range from clothes to all conceivable products suitable for online sales. Among these apps serving different fields, numerous apps that provide online food delivery are the result of the food industry's e-commerce adaptation. The use of Online Food Delivery (OFD) applications, a platform in which customers generate and receive orders via the internet (Figure 1.1), is currently common due to several factors, such as different discounts compared to physical restaurants, quick delivery for individuals with limited cooking time, and convenient access to a diverse range of flavors.

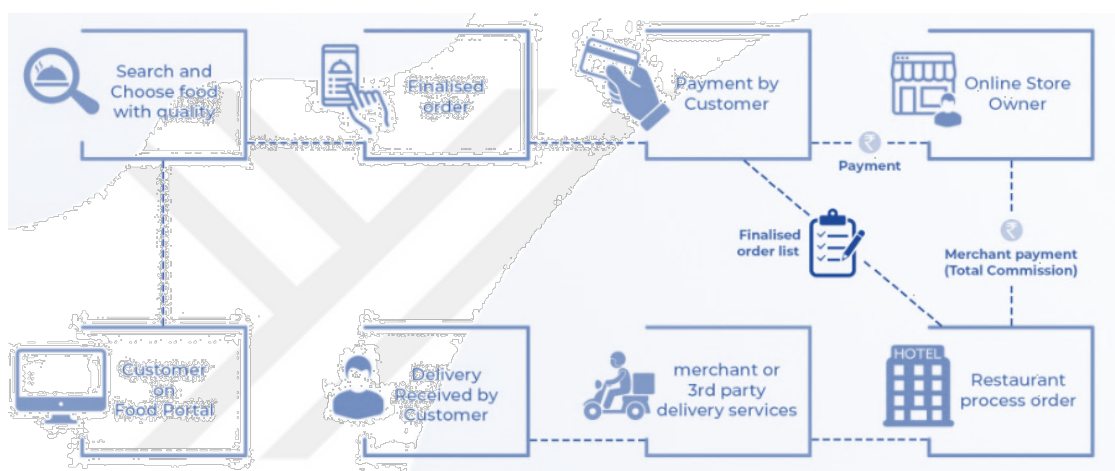


Figure 1.1. Online Food Ordering and OFD Systems [5]

According to statistics from a study conducted for the period from 2018 to 2028 [6], the number of OFD application users across the globe is expected to increase annually, reaching 2.523 million users in 2028, as can be seen in Figure 1.2. The rapid adaptation of the food sector to the OFD system, which is referred to as a cutting-edge process that enables customers to purchase a variety of food options via the platform(s) [7], could be attributed to the increasing usage rate of these apps. This increase causes significant problems in logistics management, which is one of the important parts of the process in Figure 1.1. Companies have two choices for delivering goods to customers: they may employ their fleet of vehicles or logistics network for first- or second-party delivery, or they may use a third-party delivery system, which involves purchasing resources from a third-party vendor.

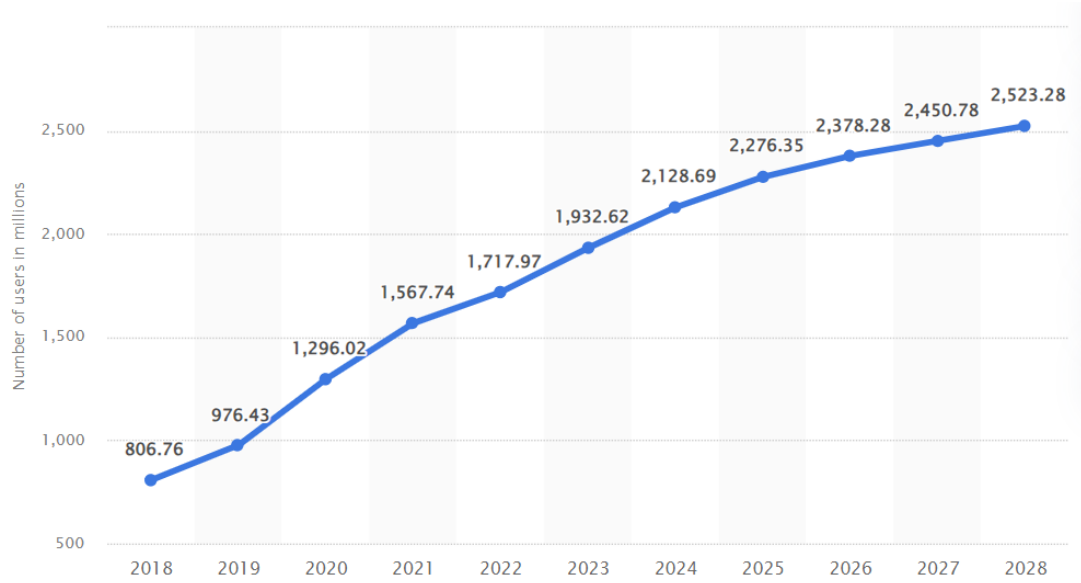


Figure 1.2. Number of OFD application users (in million) through the years [6]

Depending on the conditions, factors such as the transportation mode to be used in the system and the number and characteristics of vehicles that the company should have affect the quality of delivery service. Customer satisfaction and the company's preference over competitors are greatly affected by how quickly the order is delivered to the customer as well as not going over the time frame specified. The number of vehicles used by businesses or the frequency of vehicle usage may increase to meet the customer demands quickly and within this certain time frame. This leads to increased intensity in the transportation sector. Managing this density is therefore a major decision-making problem for companies.

1.1 Transportation

The Dictionary of Cambridge [8] defines transportation in several manners. According to one definition, it's a network of vehicles -like buses, trains, and airplanes- that facilitate the movement of humans from one place to another. On the other hand, it is also defined as moving products, such as gas, oil, etc. from one location to another. Road, sea, air, rail, intermodal, and pipeline are the six primary modes of transportation used in the commerce sector. Road transportation has been a part of logistics for longer than any other transportation network [9]. The road is the most frequently employed transportation option in logistics, as it is utilized at every stage of the supply chain.

As shown in Figure 1.3, a transport system is basically divided into three parts: the first, middle, and last mile. The term "last mile" refers to the process of delivering things from the warehouse to both the customer and the store, as well as delivering products from the store directly to the customer. In other words, it is the movement of goods the customer purchased from stores/warehouses to customers. The transport vehicle to be used in the last phase could be a van, or other alternative transport modes can also be used. Increased order volumes and transportation demands have a significant impact on the last phase of this system. Nowadays, it has been considered to be among the most costly, inefficient, and environmentally harmful parts of the whole transportation network [10]. When all kinds of needs such as clothes, home appliances, etc. are mostly purchased online, the fact that restaurants only work with a takeaway logic has also accelerated the OFD sector. This trend experienced a significant shift, though, with several regions reporting increases in OFD services: the Asia Pacific region had a 65% increase, North America had a 21% increase, Europe had a 23% increase, and Latin America had a 150% increase [11].



Figure 1.3. A basic transportation system [12]

1.1.1. Negative environmental effects of transportation

Since the absence of gasoline, diesel, or other liquid fuels throughout the developing of the initial internal combustion engines, they fueled by various gases [13]. The vehicle types that are currently utilized in road transportation include internal combustion engines, external combustion engines, and also electric, hybrid, and autonomous vehicles. Internal combustion engine vehicles (ICEVs) have been powered by different types of fuels. Diesel, liquefied petroleum gas (LPG), biodiesel, gasoline, and hydrogen are various examples of these fuels. The types of fuels also include fossil fuels. These are non-renewable resources and consist of 3

groups: oil, natural gas, and coal and 91% of vehicles operate on oil (Figure 1.4) [14].

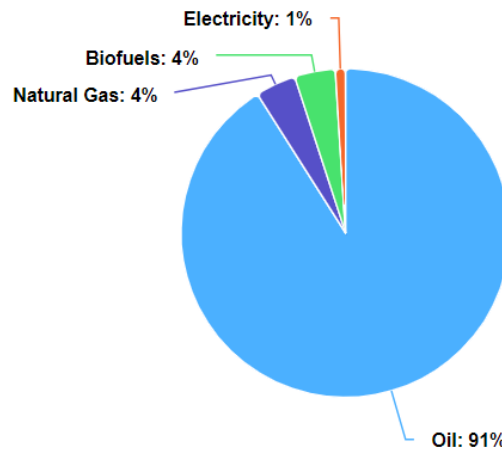


Figure 1.4. Global energy consumption in transportation by fuel in 2022 [14]

The recent increase in demand for transportation could also cause a rise in the combustion of fossil fuels. Fossil fuel combustion releases harmful substances which include sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter (PM) etc. PM refers to solid and liquid particles [15] which are one of the leading indicators of air pollution and enter the atmosphere resulting from human activities like burning fossil fuels to produce electricity, transporting goods, etc. They can easily spread through the air and change the composition of the atmosphere resulting in air pollution.

Greenhouse gases (GHGs) and carbon emissions are two separate but closely connected concepts within the environmental science context. Although carbon emissions are a primary source of GHGs, these emissions are not the same and can have various effects on the environment [16]. GHGs refer to a more comprehensive scope. They trap heat in the atmosphere and warm the earth [17]. These gases involve carbon dioxide (CO_2), methane (CH_4), nitrous dioxide (N_2O), and fluorinated gases. CO_2 is a naturally occurring gas that consists of one carbon molecule and two oxygen molecules. It is innocuous and colorless, but if large concentrations of it get into the air, it could become harmful to human health. The primary cause of the 25 billion tons of CO_2 individuals release into the atmosphere annually is human activity (of which the burning of oil accounts for 35.2%, coal for 32%, and natural gas for 12.8%. The vast deforestation of the tropical forests produces the remaining 20%) [18]. Up to

40% of CO₂ emissions are associated with urban transportation worldwide and up to 50% of significant pollutants in the air are caused by urban transportation (PM, NO_x) [19]. According to the Inventory of US Greenhouse Gas Emissions and Sinks, the main source of CO₂ emissions in 2022 was the process of transporting people and goods by using fossil fuels like gasoline and diesel, which comprised 35% of total CO₂ emissions in the US (Figure 1.5) [20]. Due to the ongoing recovery in economic activity after the COVID-19 pandemic peaked, an increase in CO₂ emissions due to fossil fuel combustion was an important factor in the increase in total GHG emissions in 2021 and 2022 in the US [21]. Since congestion in the transportation sector will also lead to congestion in the final phase, this could lead to a significant increase in the environmental damage and emissions of last-mile transportation. For instance, fast-moving consumer goods (FMCGs) have been sold through physical stores (brick and mortar). However, a rising percentage of sales are now occurring through online shopping methods and the last mile phase has been proven to have a significant impact on the GHG footprint of FMCGs [22].

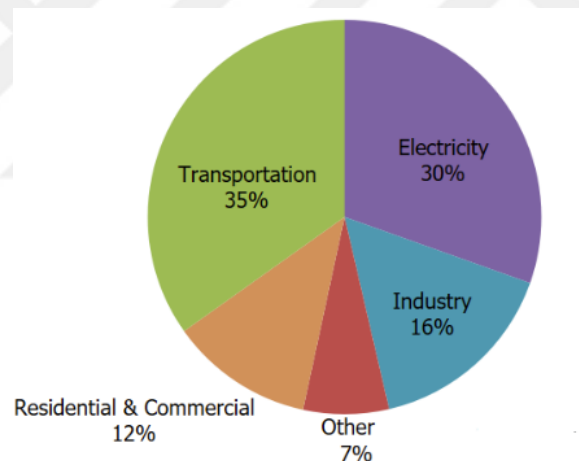


Figure 1.5. US CO₂ emissions according to sector in 2022 [20]

When these pollutants and gases are emitted into the atmosphere, they can chemically react with other gases, leading to additional harmful effects, and enter the human body through inhalation. Ingestion into the body causes harm to human health. For instance, the PM could cause breathing difficulties or certain diseases such as asthma, chronic bronchitis, etc. SO₂ may worsen pre-existing lung and heart problems and lead to respiratory diseases. In addition, diseases caused by certain air pollutants, such as heart disease, stroke, lower respiratory infections, lung cancer, diabetes, and chronic obstructive pulmonary disease (COPD) are just a

few of the major causes of death that are at risk due to air pollution. According to a report released by the independent nonprofit research group Health Effects Institute (HEI) in the US, 8.1 million fatalities were attributed to air pollution globally in 2021. In addition to these fatalities, millions more people suffer from chronic illnesses, placing a massive strain on economies, societies, and healthcare systems [23].

The production and burning of fossil fuels for energy and transportation has resulted in the annual release of billions of tons of CO₂ and over 120 million metric tons of methane into the atmosphere in recent years [24]. Fossil fuel extraction, processing, and transportation can lead to oil spills that endanger human and wildlife populations, devastate habitats, erode shorelines, and force a shutdown of parks, beaches, and fishing areas. More specifically, SO₂ can harm fragile ecosystems and streams, as well as harm trees and other plants and prevent plant growth [25]. Through chemical interactions in the air, NO₂ causes acid rain, which destroys fish, animals, and forests. Atmospheric processes that result in ground-level smog and ozone also heavily depend on NO₂ [26]. Due to the fact that vehicle exhaust is the main source of NO₂, urban areas that are densely populated -especially those in high-income nations- often experience the greatest levels of exposure to NO₂ and its negative health effects [27]. In addition to the air and water pollution caused by fossil fuels and the threat to the lives of living beings posed by the gases emitted, the increasing demand for transportation is also expected to cause noise pollution and traffic congestion that will disturb society and decrease their life quality who live in highly populated countries or those that are developing may be more affected by these negative consequences. Increased traffic density can also have psychological effects such as tension and unhappiness in people living in crowded cities.

There is a growing concern among individuals and companies about the health and social issues associated with the rise in transportation and air pollution. By implementing regulations to address these concerns, some governments could attempt to minimize the detrimental effects of the transportation sector. They are intended to assist environmental protection initiatives and encourage the transportation sector to be environmentally friendly via employing emission standards, fuel quality regulations, public transportation incentives, and the construction of bicycle and pedestrian pathways. These regulations can be implemented to encourage the usage of greener fuels or public transportation to reduce car usage by building and improving bicycle

and pedestrian paths. They also aim to increase the use of renewable resources or electricity-powered vehicles instead of fossil fuels. Apart from governments, for logistics service providers, the growing volume of small-sized shipments and the fluctuations in their frequency triggered by the expansion of e-commerce provide a significant problem [28]. The use of traditional methods by service providers has raised many subjects which can be referred to as conventional delivery challenges. It includes workforce, demand and expectations, costs and sustainability issues (Figure 1.6). Traffic congestion, environmental impact, fleet and fuel expenses are the subheadings that need to be managed.

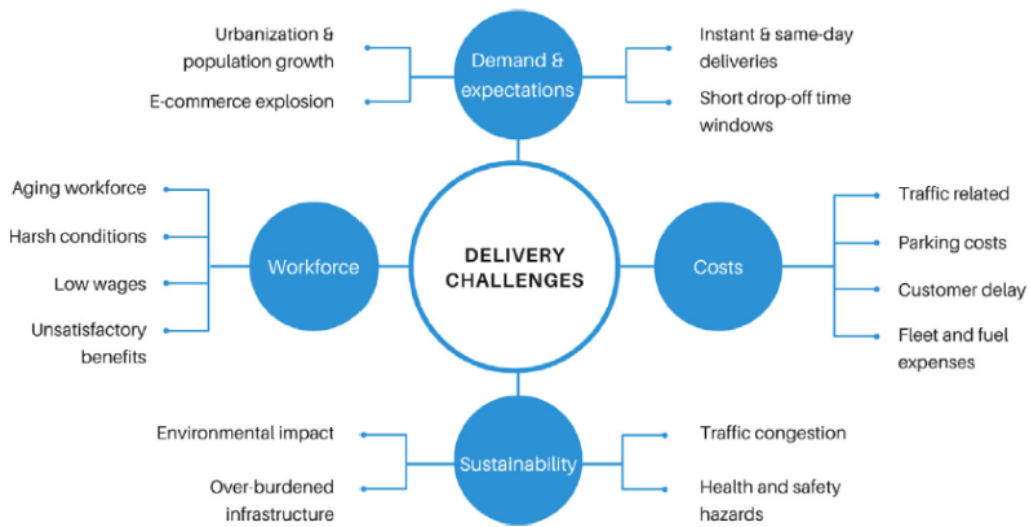


Figure 1.6 Conventional delivery challenges [29]

1.2 Green Transportation

Transport has become more dependable, efficient, and ecologically friendly with the development, assessment, and application of new technology [30]. The use of environmentally friendly vehicles, or green vehicles has become one of the most important measures in the last mile. Green transportation (GT) is defined as transportation that has fewer adverse effects on the environment and human health than other forms of transportation [31]. It can be regarded as an approach that utilizes electric vehicle (EV) technology effectively, using biogas as a fuel, employing public transportation, and ensuring the most effective use of conventional fuels. [32]. EVs are regarded as an advanced technology that can help reduce overall urban emissions of noise and pollutants because they emit no local emissions [33].

1.2.1. Alternative GT vehicles to traditional vehicles and their applications

The two primary categories of electric vehicles (EVs) are (i) light EVs, such as electric motorcycles (e-motorcycles) and scooters and (ii) heavy-duty and medium EVs, such as electric trucks and e-cars [34]. E-motorcycles are becoming increasingly common because of many advantages, including their portability and compact form. They could reduce harmful emissions while offering fast movement in urban areas with congestion. Mid-drive motors consume less battery power, which makes them more user-friendly [35]. Compared to traditional petrol-powered bikes and scooters, they have a few moving components and mechanicals. Additionally, they don't need air filters or engine oil, which are the parts of ICEV and have to be changed frequently. Thus, only the most basic components require repair. In addition, there are two key cost benefits associated with electric two-wheelers: they require less maintenance over time and have more predictable energy costs. E-motorcycles generally less expensive due to their electricity-powered operation. And electricity exhibits less price volatility compared to gasoline and diesel [36]. Transporting with e- motorcycles is generally suitable for daily use or small-scale transportation requirements. The lighter weight and smaller volume of meals and beverages compared to many other products make these vehicles used in food delivery more common with their carrying bags. Thermal isothermic bags are another tool utilized during food shipping to preserve food, whether it is hot or not. For instance, in 2021, Yemeksepeti, one of the e-commerce sites in Turkey, started to make some of its deliveries with an environmentally friendly electric motor field team.

One of the environmentally friendly innovations can be autonomous robot usage in the delivery system by utilizing electrical technology. These robots can be divided into two groups according to their use: Sidewalk autonomous delivery robots (SADRs) and road autonomous delivery robots (RADRs). SADRs are robots the size of pedestrians that exclusively use sidewalks or paths for pedestrians. On the other hand, RADRs move on shared roadways with traditional vehicles [37]. Startups are testing autonomous delivery robots (ADRs) in many US cities that travel sidewalks and roads. In 2021, Amazon's in-house Scout program was marketed by the company as a way to continue deliveries in the event of COVID shutdowns to make deliveries [38]. In March 2016, The United States-based pizza giant Domino's Pizza Inc. released market an autonomous pizza delivery vehicle that is claimed to be the first in the world. This vehicle was called Domino's Robotic Unit, or "DRU" [39]. Another application is that with

a fleet of 25 robots from Starship Technologies, George Mason University the initial university campus which involves robot-delivered food as part of its meal plan (Figure 1.7). In addition to food delivery, SADR and RADR can also be utilized for specific purposes in the health sector as a healthcare logistic robot for medicine delivery or at hotels as a room service in accordance with its structure.



Figure 1.7. The Starship robots which provide food delivery to about 400 students on campus [40]

Increasing demand for delivery has led to a focus on delivery that is both faster and more affordable. One of the groundbreaking innovations in this sector is drone usage powered by electricity, also known as Unmanned Aerial Vehicles (UAVs). Drones have a long history of use. The first drones were often developed for military purposes. The first military drones were used for reconnaissance and target acquisition during the Second World War. They were usually remote-controlled and UAVs. For example, in 1946, a prototype remotely operated drone built on a B-17 Flying Fortress aircraft departed Hilo Naval Air Station in Hawaii and flew to Muroc Army Air Field in California. In the early 2000s, they began to be used for commercial and civilian purposes. In particular, they became popular in fields such as photography and videography. Towards the mid-2010s, drone technology began to develop rapidly. Smaller, lighter, and more user-friendly drone models were launched. During this period, drones became more common in commercial and civilian applications. In the late 2010s and early 2020s, the use of drones for leisure activity purposes, like aerial videography, increased. At the same time, their application in industries became widespread and they have become widely used in agriculture, search and rescue, construction, security, and transportation.

Drones have drawn too much attention due to their high job endurance, improved stability, low cost, and great mobility [41]. Also, this technology is used to replace humans in areas that are dangerous or difficult to access. For instance, they can be used in fields that are difficult for people to physically reach to quickly and effectively collect data or to do inspections where hazardous chemicals are present. Their ability to reach inaccessible places also allows them to be used for environmental monitoring and protection tasks, such as monitoring natural disasters and tracking environmental changes. They provide higher cost reductions and faster reaction times as they are employed to map disaster zones than traditional methods offer. In order to coordinate rescue tasks, drones could be deployed quickly, offer three-dimensional (3D) mapping with high resolution, locate hotspots having the most harm, and upload data in real-time. On the other hand, the pandemic has exposed a number of long-hidden health inequities. Drones have made it possible to deliver immunizations to low-income nations [42]. In addition, during the pandemic, social distancing, border closures, avoiding large crowds, contactless transit, and quarantine were crucial strategies. To combat this infection, some countries used digital, wireless, autonomous, and other innovative technology including UAVs because they minimize human functions [43].

Drone technology is currently being used in various industrial fields, including building and construction, real estate marketing, the public sector, visual inspection, solar panel inspection, managing road construction, railway inspection and monitoring, and transportation [44]. Several nations and organizations have become interested in employing drones for e-commerce. A primary reason is the possibility of enhanced performance and output. They could offer a much-needed upgrade to the current postal and shipping systems, which are frequently unreliable and slow [45]. Due to the useful size-to-weight ratio of food items and the short trip duration of UAVs, which are favorable for fresh food delivery, food delivery operations are one of the primary application areas of drone technology. Domino's Pizza in collaboration with Flirtey used SkyDrop drones (Figure 1.8a) for delivering pizza in New Zealand in 2016 [46]. In 2022, Yemeksepeti delivered food to ships via drone (Figure 1.8b) [47]. Within less than ten minutes, pizza could be delivered by drone due to autonomous control via GPS navigation and qualified drone pilot supervision. Similar to these, in 2014, Francesco's Pizzeria dropped pizzas on high-rise buildings' rooftops in Mumbai via drones to deliver pizza [48]. After Silicon Valley

startup TacoCopter revealed its intentions to use drones for carrying tacos throughout the City of San Francisco in March 2012, the announcement was widely reported. Customers who are interested can place their orders through a smartphone app, and comfortably wait as a drone delivers their food to them from above [49]. LaMar illustrated the usage of drones for the delivery of doughnuts to the fire, police, and city hall departments in Denver, Colorado [50]. Also, Coca-Cola, a beverage company in the food industry, investigated employing drones to distribute Coke to over 2,700 workers on construction sites in Singapore [51].



Figure 1.8. a) SkyDrop Drones for Domino's pizza delivery [52]

b) Food delivery by drone to a ship [47]

Parcel delivery is another area where drones can be used. DHL demonstrated its autonomous DHL Parcelcopter 3.0 drone system, which can be used to carry packages to locations that are difficult to reach. These drones can ascend vertically and change into a horizontally traveling airplane, enabling them to travel at speeds exceeding 43 miles per hour. DHL would have reduced the typical delivery time from the base to the delivery location from 30 minutes by vehicle to 8 minutes by drone by using this autonomous system [53]. In less than 30 minutes, Amazon tested a drone prototype that can deliver products weighing less than five pounds to customers; between 75 and 90 % of Amazon deliveries weigh under five pounds [54]. Groceries were delivered from a Yokosuda store to an island three kilometers offshore by the Japanese internet merchant Rakuten [55]. These drones can carry various kinds of goods up to 5 kg and can travel 36 km/h for up to 40 minutes. A quadcopter drone was used by the Irish drone firm Manna29 to transport payloads weighing between 2 and 4 kg [56].

There are also applications of use in the health sector. In an effort to assist healthcare facilities and hospitals, the government of Ghana officially introduced its drone delivery service in April 2019 in collaboration with the US startup Zipline [57]. Developing an emergency on-demand vaccine, blood product, and drug delivery service was the objective. Drones were used by the company Zipline to transport 1400 blood samples daily on average to hospitals within 75 kilometers of a distribution facility in Muhanga, Rwanda [58][59]. This technology assisted in reducing delivery times from 4 hours to less than 30 minutes owing to their speed because these drones can reach speeds of about 80 miles per hour [60]-[62]. They can also be used in emergencies, as they are fast and can reach inaccessible areas with road problems. For instance, in 2012, after an earthquake hit Haiti and the Dominican Republic, Matternet used drones to provide supplies for people in need [63].

Innovative vehicles like electric motorcycles and drones have proven their ability to carry deliveries, as evidenced by these various applications. By utilizing these vehicles, which can be used as an alternative to traditional delivery vehicles, an environmentally friendly transportation system is aimed. The IEA's Net Zero Emission scenario predicts that the transportation sector's global emissions of more than 7 Gt CO₂ in 2020 will drop to 5.5 Gt CO₂ by 2030 and 0.7 Gt CO₂ by 2050. In addition to reducing environmental damage, reducing costs and travel time is among the objectives. Their ability to move in 3D allows them to shorten the distance and time when traveling on a straight route. This means that with direct transportation they could eliminate the additional costs of intermediate transfers or intermediate points. Using sophisticated dynamic automation systems or pre-programmed flight plans, remote control software on a computer allows drones to operate autonomously [64]. By performing certain tasks automatically, they could reduce labor and operational costs. Since it can be pre-programmed and remotely managed and no need for personnel such as couriers are among the features that encourage companies to use this technology in transportation. Drone usage as an alternative environmentally friendly vehicle has exciting potential to enable more sustainable, efficient, and less last-mile cost solutions in this sector. Also, it can be advantageous in areas with heavy traffic or dispersed settlements.

1.2.2. Importance of utilizing GT vehicles in last-mile transportation

The use of green vehicles in the last mile as an alternative to conventional vehicles is necessary for several reasons. Because green vehicles have electrically powered or low-emission engines, they could also reduce negative environmental effects when used for last-mile transportation. The industrialized world is becoming more committed to electrification as the primary means of achieving a significant decrease in emissions from road transportation [65]. The future use of EVs in distribution is being encouraged by the need for low- or zero-emission transportation in last-mile delivery, which is being driven, for example, by market demand or regulations. It is expected that they will become more advantageous from both a technical and financial standpoint for last-mile delivery, depending on developments in technology, politics, and customer demand [66]. The Sustainable Development Goals of the United Nations outline how humanity can slow down climate change and protect our environment, which includes everything from forests to oceans and all points in between. They emphasized cutting overall annual carbon impact by up to 2 tons of CO₂e by converting vehicles that run on gasoline or diesel to electric ones and CO₂ emissions by up to 700 kg by utilizing a hybrid vehicle [67]. The shipping cost per item rises as the product approaches its ultimate location, culminating in the last phase. This is also known as the "last mile challenge" that logistics companies, especially their online retailers deal with [68].

In general, electric vehicles require less energy and maintenance than traditional internal combustion vehicles. Compared to fuels, the price of electricity frequently remains more stable and can be less expensive. This could result in fuel and maintenance cost savings for customers. According to another study by Schöder [66], compared to conventional powered vehicles with ICEVs, the operating costs of EVs also have the potential to be lower.

Since internal combustion engines operate through an explosive combustion process, there is more noise produced by the exhaust system and the friction of numerous moving parts. In contrast, EVs are quieter because they don't have internal combustion engines and have engine designs with fewer parts. The usage of these vehicles could play an important role in reducing noise pollution.

Many autonomous delivery robots (ADRs) are one of the important developments brought about by technology and the need for contactless delivery during the pandemic and they run on electricity. This eliminates the combustion emissions of fossil fuels including diesel and gasoline. They are one of the environmentally friendly vehicle options that reduce the emission of harmful gases. Automation enhances the efficiency of the delivery process and reduces road congestion compared to manual vehicles. Reduced traffic leads to a decrease in the frequency of stopping and starting, resulting in reduced levels of fuel consumption and emissions. In certain situations, they have the potential to save expenses and shorten the time it takes to deliver.

ADR-aided deliveries are found to save significantly more time when compared to traditional deliveries, especially when tighter windows are put into consideration [69]. When time windows are present, ADR-assisted deliveries may reduce up to 89% of the cost of traditional deliveries [70]. Additionally, a 75% reduction in the quantity of customers that are delayed occurs when the ADR speed increases from 5 to 6 km/h [71].

While reducing emissions, UAVs can be used in situations such as making deliveries to inaccessible places and providing fast transportation in emergencies. They can be used alone or in synchronization with other vehicles. Delivery times might be decreased and CO₂ emissions could be reduced by operating drones and other modes of transportation together. Due to their high level of automation, electric drones are a more economical option than road-based modes of transportation such as diesel vehicles and EVs. Compared to delivery in rural areas, large drones emit fewer pollutants than diesel trucks [72]. For parcel delivery, a method that only utilizes trucks is the least effective type of transportation out of the three available modes - drone usage gradually, relying solely on trucks, and a hybrid truck-drone transportation system. In fact, of all the transportation options under consideration, it has the highest cost, contamination, and congestion. Every customer can be served by a hybrid transportation system that uses vehicles connected with drones, despite the challenges related to using all of the benefits that drone technology provides [73]. To transport packages, employing UAVs could be a way to reduce fixed costs by lowering the amount of time necessary for delivery and the number of vehicles required. In addition, it could lower variable expenditures, namely the fuel costs. Thus, there is potential to decrease fuel use substantially and the ensuing carbon

emissions. The delivery of fast food meals and small consumer goods by drones has the potential to improve urban mobility significantly. For quick-service restaurants and e-commerce businesses, drones offer an agile and sustainable form of transportation, particularly when big volumes of high-speed deliveries are needed [74]. In addition, the use of lighter materials or the adoption of more efficient engine technologies can improve energy efficiency as technology advances. Drone-based delivery has the potential to lower energy consumption and greenhouse gas emissions in the freight industry if implemented properly. For instance, drones are significantly more advantageous than delivery vans or trucks that run on diesel and CNG since they are powered by low-carbon electricity [75]. Because drones are generally smaller and lighter, they consume less power. This means less energy use and therefore less harmful gas emissions compared to traditional means of transportation. They usually fly directly from one point to another and are not subject to intermediate routes or traffic congestion. This allows for a more efficient transportation process and therefore results in less energy consumption.

1.3. Customer Environmental Awareness and Preference Tendencies Towards Green Brand Image

The development of technology and the faster dissemination of information has raised awareness of air pollution among many customers and encouraged them to contribute to reducing the significant harmful effects of transportation on the environment. For this reason, the company's ecologically beneficial practices have also become important when choosing the companies. Green vehicle options for deliveries could be a crucial component of the image that shows customers and the general public a more sustainable business plan for companies that want to reduce their environmental effects and meet their sustainability goals. Online retailers aim to ensure that customers have a gratifying experience at every step of the purchasing process, from they order the items until they are delivered or picked up. This is due to their need to protect their company's positive reputation and encourage customer loyalty, which is also known as their "green brand image" [76][77]. A green image is the perception that customers have of a brand's environmentally conscious activities and products, which are usually considered more significant than the environmental initiatives of its competitors [78]. Hwang and Kim's study attempts to determine the significance of a green image with regard to drone food delivery services. It was specifically suggested that the favorable perception of drone food delivery services stems from their environmentally friendly image [79]. M.K. et al.

indicate that customers are willing to pay extra for e-commerce delivery if green delivery is assured and sustainable delivery factors are valued [80]. As a result, building their green brand image is important since buyers consider this an essential factor in their decision-making process when purchasing goods or services.

1.4. GHG Emissions of EVs

Electricity-powered alternative modes of transport do not use fossil fuels and therefore do not release harmful gases into the environment during travel but this does not mean that electric vehicles have not any GHG emissions. The carbon emissions of these vehicles depend on various factors. The production of batteries for electric vehicles often has high energy consumption, which could result in detrimental effects on the environment. When batteries for electric vehicles are manufactured, a significant amount of CO₂ is generated. The manufacturing of lithium-ion batteries is mostly responsible for this. The composition of batteries includes various rare earth elements, and the extraction could release carbon emissions. A 2018 International Council on Clean Transportation (ICTT) analysis states that the composition of batteries and the countries in which they are produced have a significantly greater effect on emissions [81]. At the end of the life of the vehicles, it is also important to recycle and reuse the batteries. These batteries' reuse in different areas has proven to be technically and economically feasible [82]-[84]. Recharging the battery is another feasible method for this issue. If recharging occurs adequately and quickly, it could result in faster delivery and less GHG emissions than exchanging the battery [85]. According to Net Zero 2053 Turkey Electricity Roadmap for the Sector, most of the investments in the energy sector will be directed towards restructuring the electricity system to be predominantly based on renewable energy sources. Energy efficiency practices in all sectors, along with renewable energy, lead to lower energy intensity and carbon emissions in production. Providing an important substitute for fossil fuel use, electrification is highly energy efficient and plays a critical role in decarbonizing the energy system. In the transportation sector, for example, model results show that increasing the share of electric vehicles is the main driver for energy efficiency. Electric vehicles are significantly more efficient, losing only around 10% of the electricity supplied, while conventional internal combustion engines lose around 80% of the energy [86].

1.5 Problem Definition

The pandemic and technology have accelerated the concept of e-commerce, which has led to a shift in buying habits from traditional brick-and-mortar stores to online stores. This technological development results in a rise in demand for product purchases and customer delivery while providing advantages like enabling customers to browse the same product across various sellers and compare their prices, as well as the ability to buy it anytime they desire. In order to stay ahead of the competition and increase their sales, companies aim to increase customer satisfaction by offering the best and fastest possible delivery to customers. These reasons could significantly increase the vehicle density of the last phase of the transportation system where the order reaches the customer, i.e. the last mile transportation, and consequently the harmful effects on the environment combustion of fossil fuels used. As a result, this could endanger the health of all living beings on Earth. The widespread and rapid development of technology has accelerated people's awareness of this problem. Also, the fact that many customers are now aware of this problem has led them to give importance to the green image of the companies while choosing the company they buy the product from. Companies currently pay attention to factors such as environmentally friendly products and GT in order to increase their preferability and reduce the damage that last-mile delivery may cause to the environment. At the same time, companies prioritize the reduction of their expenses as one of their key considerations. Technology-supported EVs like drones, e-motorcycles, robots, or engines powered by alternative fuels that can emit less pollutants than fossil fuels have all started to be utilized as alternatives to conventional ICEVs under the GT concept. These technologies also stand out because the price of electricity is less changeable and more acceptable than the price of fossil fuels like gasoline. Another advantage is that, unlike other vehicles, they do not use roads, so they are not affected by traffic and offer the quickest delivery times. They can deliver to inaccessible areas without roads.

To integrate EVs into their transportation systems and take advantage of their time and cost reduction, and environmental benefits, businesses need to decide which vehicle to purchase in quantity according to the order parameters such as travel distance, order weight, etc. According to the characteristics of the EVs, certain limitations also need to be managed when firms decide to incorporate them into their systems to make deliveries. Constraints such as the carrying capacities and range of the vehicles need to be taken into account when deciding which order

needs to be delivered by which type of vehicle in order to minimize environmental impact and costs. It is necessary to determine the number of vehicle types that should be purchased when considering these constraints. Otherwise, solutions involving the utilization of eco-friendly vehicles that are not appropriate for the current circumstances would emerge and companies would be spending their resources in the wrong direction. Therefore, the decision of how many of each type of vehicle, including all these constraints, has to be modeled.

1.6. Purpose of the Study

While utilizing conventional delivery methods, specifically ICE motorcycles, the company has burned fossil fuels to deliver orders, resulting in the emission of hazardous gases into the atmosphere. This study aims to suggest alternate forms of transportation, including e-motorcycles and drones, with the objective of minimizing environmental harm and delivery costs. In order to incorporate these EVs into their transportation system, the corporation also took into account factors such as payload capacity and vehicle range. An optimization-simulation model was developed based on these characteristics to calculate the optimal number of cars for various scenarios. The optimal scenario was identified using the The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach, accounting for the investment costs of the various scenarios in addition to the delivery cost and CO₂ emission minimization objective functions considered in the optimization-simulation model.

1.7. Steps of the Study

This study was conducted in 9 steps in the scope of the thesis.

- i. **Identifying the problem:** This is the process of determining the problem to be addressed. It is the step where the parameters and required information are gathered.
- ii. **Review of the previous studies:** This is the process of reviewing the literature on last mile transportation and green transportation vehicles. This is the step where solution approaches and formulations of these subjects in the literature are examined.
- iii. **Defining the Problem:** This is the process of defining the problem to be solved within the study's context. This is the step where the required parameters and decision variables related to the problems are identified.

- iv. **Developing the Simulation Model:** This is the step where the simulation model is developed for the solving the problem and integrated into the package program to be used.
- v. **Solving the Simulation Model:** This is the step in which the simulation model is solved.
- vi. **The Simulation-Optimization Model:** For the simulation-optimization model, this is the step where the optimization model is integrated into the simulation model.
- vii. **Analyzing the Scenarios:** This is the step in which scenarios for different vehicle types are analyzed in the simulation optimization model.
- viii. **Selecting the appropriate scenario:** This is the step where the scenarios are prioritized according to the results of the simulation optimization model and different parameters and the appropriate scenario is selected by MCDM.
- ix. **Analyzing the Results:** This is the step where the results obtained from the solution of the problem are evaluated and recommendations are provided for future studies.

1.8. Organization of the Study

In the following sections of the study, the literature on transportation models and last-mile transportation is presented in the second section. The third section includes the proposed simulation model, the simulation optimization model, and the data used in the study. The fourth section provides the findings and analyses obtained for the developed approach. In the last section, the findings and results are discussed and recommendations for future studies are given.

2. LITERATURE REVIEW

In this section, a literature review was conducted methodically and was grouped under 3 sub-headings. The first sub-heading includes the integration of alternative transportation modes into the last mile and is grouped under 3 sub-subheadings. The groupings consist of studies that investigate and compare the advantages and disadvantages of a pure (single) vehicle, combine and examine different types of vehicles, and evaluate and compare different transportation modes. Other sub-headings include the determination of negative environmental effects of other various factors, and the identification of customer behaviors, tendencies and preferences in green transportation and green brand image respectively.

2.1. Integrating Alternative Transportation Modes into the Last Mile

2.1.1 Investigating and comparing advantages and disadvantages of a pure (single) vehicle

Rabta et al. [87] offered an optimization model for delivering multiple packages of lightweight relief supplies, such as vaccinations and water purification tablets, using drones. The model considered the technological requirements of drones and specific disaster-related conditions. The researchers also investigated drone usage in last-mile distribution for humanitarian logistics. The proposed model considered the drone's energy usage concerning its payload and flight mode particularly. The challenge of using one or a fleet of identical drones (UAVs) to transport numerous packages of lightweight humanitarian supplies to remote locations was considered. There were three separate sets of geographical places identified. The depot was represented by the letter D in the first one. The researchers assumed that drones began flying at a single base station, where D was a singleton set. Set P was divided into priority subsets based on a predetermined number of priority levels and included demand locations. Lastly, set R included a representation of recharge stations. The model analyzed the following constraints: degree, demand, energy, and priority. In addition, the study provided numerical examples to demonstrate how to use the optimization model using the GAMS (General Algebraic Modeling System) optimization engine. Then, the model calculated four scenarios in which the drone's maximum energy level and payload capacity change. These examples demonstrated how the

drone's energy consumption function could influence the ideal solution to the suggested routing problem.

Using the life cycle impact assessment (LCIA) approach, Koiwanit [88] presented a life cycle assessment study conducted in Thailand on delivery via drones using the drone model CML2001. This study included coal mining, electrical generating station operations, drone raw materials, drone manufacturing, and drone use phase. The primary focus was on the 11 environmental effect groups, such as global warming potential (GWP), and the study discovered that while drone operation had the smallest effect across all impact categories, part manufacture had a major effect on environmental issues. The primary causes of abiotic depletion, global warming, and other problems were coal mining and the operation of electricity-producing stations.

For electric vehicles, a fleet size and mix vehicle routing problem with time windows were established by Lebeau et al. [89] to investigate the potential integration of electric vehicles in urban logistics activities. The study utilized the real-life example of a supplier that had a depot in Brussels to focus on the current state of an urban distribution center based on a vehicle routing problem (VRP) that the researchers developed. The fleet size and mix vehicle routing problem took into consideration various vehicle sizes that run by internal combustion engines or electricity. FSMVRPTW-EV was the name assigned to the problem formulation, describing a fleet size and mix vehicle routing problem with time windows for electric vehicles. The duration, distance, and date of each BEV's travel were monitored from December 2012 to December 2013. The energy used and recovered during the trip was also recorded. Using an ordinary least squares method, the researchers modeled the energy usage based on the information provided. The findings indicated that a fleet with various technologies reduced distribution costs. Electric vehicles were frequently the most competitive technology in the quadricycle and small van markets. Since hybrid vehicles had lower fixed and operating costs than diesel trucks, they were mostly chosen in the truck markets. Hybrid vehicles derived advantages from reduced maintenance expenses and increased savings through tax deductions on profits. The findings additionally suggested that electric vehicles' constrained range was appropriate for urban distribution.

Balaban et al. [90] offered a theoretical constructive simulation model and gave a hypothetical scenario for UAS delivery business operating models. The full factorial design simulation analysis was used to estimate the causal links between several independent and dependent business and policy factors, such as drone velocity, flying altitude, drone number delivery demand, route type, maximum drone fly-time, number of completed orders, time average drone density, order time, drone utilization, and customer accessibility. The investigators' objective was to investigate what would be necessary to develop business solutions that could be customized for a UAS delivery system. Three Modeling and Simulation (M&S) techniques were taken into consideration during the preliminary investigation of the future UAS delivery system: state charts (SC), agent-based modeling (ABM), and discrete event simulation (DES). In this study, the investigators only investigated the following two routing approaches. Route type (RT) first simulated a traffic system that was based on vehicles and in which drones fly over the roads. Drones flew right toward customers in the other approach. To investigate the causal relationships between the independent and dependent variables, a business scenario involving a single company receiving orders from a population of customers -which were subsequently fulfilled by delivery drones- was generated through the simulation model. Order processing-related product deliveries were represented by DES, while order processing-related resources were represented by UASs. The characteristics of entities and agents were combined in orders and UASs. ABM allows for the embedding of processes, behaviors, and interactions of players (such as delivery companies, customers, orders, and drones) in the overall multi-level model structure.

Gruber et al. [91] investigated the viability of electric cargo bikes (E-CBs) in urban courier services, the structure of the market as it existed at that time, the opinions of bike and vehicle messengers toward electric cargo bikes, and the factors influencing their tendency to utilize them. To acquire a qualitative understanding of the current organization of courier services, their employment and remuneration structure, and the type, cost, and financing of used vehicles, expert and group interviews were conducted with the CEOs, dispatchers, and messenger supervisors of the 8 German courier companies. The researchers interviewed all 590 couriers from the eight participating companies to determine their willingness to use an E-CB as a mode of transportation for their daily courier job. The mode of transportation and shipment type were utilized to filter the sample for this study. Like most courier services, there are two main

shipment types offered: point-to-point shipments and overnight deliveries to any domestic or foreign location, where messengers bridge the first and last mile. In addition to the geographical expansion of courier services, the researchers investigated other distinctions between the two modes and the implications for potential E-CB use, such as shipment distance, goods weight/volume, and the temporal characteristics of demand for courier services. The results showed that in addition to transportation distance, the weight and volume of the products could also affect how competitively different courier services are. E-CBs could carry all bike deliveries and 85% of car deliveries if volume and weight were the only restrictions. Given the greatest shipping distance threshold of 10 km and limited to products that fit within the cargo box in terms of weight and capacity, the following is how the E-CBs' technical potential could be determined: Car shipments would be replaced by E-CBs in 42% of cases. Given that electric support could be provided for pedal electric vehicles (Pedelects) up to 25 kilometers per hour, it appeared feasible that E-CBs could reach a comparable cruising speed to satisfy the timing limitations of the markets. The findings also suggested that E-CBs could be a viable option for transporting greater loads while reducing fuel and maintenance costs.

Garg et al. [92] carried out a comprehensive analysis of 55 multidisciplinary studies to examine the current state of drone applications for last-mile delivery. Specifically, the study focused on three main areas: improving customer accessibility through drone usage, the potential cost savings and carbon reduction associated with drones, and the situations in which drones are more effective than traditional delivery methods like trucks and electric vehicles. Six databases were reviewed: ABI/Informs, PubMed, ScienceDirect, Scopus, TRIS, and Web of Science. According to the analysis, across 24 different countries, with 21 studies the United States was in the lead, followed by Australia with three, China and Italy with four each. Each of South Korea, India, and Canada contributed two studies. The remaining countries had one study each, such as Madagascar, Austria, Brazil, Turkey, etc. The studies also found that evaluating the time and operational costs related to drone delivery was often the top priority for researchers. However, the benefits of drone deliveries in lowering carbon emissions were the subject of relatively little research. It was also mentioned that in densely populated locations, reducing noise pollution and environmental effects could be a more important goal than delivering on time or keeping costs low.

Moshref-Javadi et al. [93] comprehensively classified, reviewed, and analyzed 101 publications focusing on utilizing UAVs for last-mile delivery of goods to customers and their design features. The study also defined six additional criteria, such as the number of primary vehicles, and presented numerous enhancements to the basic classification framework (pure-play drone-based (PD) models, etc.).

2.1.2. Combining different types of vehicles

Goodchild and Toy [94] evaluated the vehicle miles traveled (VMT) and carbon dioxide (CO₂) emissions of two delivery models: one that used trucks and the other that used drones. To achieve the study's objective, simulations of various scenarios were made, where parcels were delivered to customers' addresses in circular service zones by trucks and drones that begin from a central depot. Algorithms and emission constants were provided via simulations, along with estimates of VMT and CO₂ emissions that would be compared between delivery alternatives. Ten scenarios with varying recipient densities were developed in order to examine if the density of recipients affected the comparison analysis's results. These trucks were likely fueled with diesel, and all deliveries were conducted in a free-flowing, unrestricted manner. The goal of the research was to calculate the amount of CO₂ that drone electricity demand would cause energy-generating facilities to emit. Within a framework of operational and logistical presumptions, using several ArcGIS tools and emission criteria, two models were compared. The findings showed that, in general, trucks were a better choice in terms of generating less CO₂ when the average energy need of a drone increased. Additionally, additional emissions were produced at power-producing facilities since charging a drone requires more electricity. In service zones that were either closer to the depot, had fewer recipients, or both, drones emit fewer CO₂ emissions than trucks.

Hur and Won [95] found that combining drones and trucks for last-mile parcel delivery reduced CO₂ emissions and delivery times. The investigators conducted a sensitivity analysis to improve delivery drone flying performance in a drone-and-truck delivery strategy. Each distribution point consisted of multiple delivery zones (clusters), and drones were loaded onto trucks as they moved between them. Drones carry one item in a single trip by moving directly from the starting point to the destination. There were four scenarios for delivery: diesel trucks solely, diesel drones and trucks combined, EV trucks only, and EV trucks combined with drones. CO₂ emission and delivery time variance, CO₂ emission for varied drone range limitations for

EV trucks and diesel trucks with drone delivery, truck CO₂ emission variations between EV trucks and diesel trucks, and CO₂ emission and delivery time variance by cluster number were all examined and compared. The results revealed that using drones and trucks together could reduce CO₂ emissions while shortening delivery times. This was accurate for both diesel and electric trucks. Furthermore, after drone delivery ranges were changed and compared, increasing delivery distance resulted in significantly less CO₂ emissions. In particular, the maximum effect was confirmed by reflecting the potential of straight movement, and distinction was ensured by comparing delivery times.

Lemardelé et al. [96] primarily aimed to calculate the operating expenses of the carriers for the two different delivery systems through the Continuous Approximation model. Initially, a ground autonomous delivery device (GADD) and an urban consolidation center (UCC) were combined. Up to 25 items could be delivered by the robots on each route in the study. Drones for air delivery launched from trucks were employed in the second approach. Throughout the service region, trucks performed numerous stops at fixed points from which drones could be launched repeatedly. One delivery was expected to be made by each drone at a time. Lastly, an extensive analysis of the externalities, which were Well-to-tank (WTT), Tank-to-wheel, Vehicle production externalities, and the impact of the vehicles on the urban infrastructure, generated from each delivery pattern was conducted. Using continuous approximation equations, the operational costs and externalities resulting from GADDs in relation to a UCC and truck-launched unmanned aerial vehicles (UAVs) were calculated. To calculate overall operating cost and externalities emissions, four possible delivery strategies were examined and contrasted. Many inputs, including the size of the service area, the distance between the carrier and the distribution center, and the technical specifications of the vehicles, GADDs and drones were considered. Once everything was considered, it was obvious that autonomous technology could reduce the costs and externalities related to last-mile operations. When comparing business-as-usual delivery patterns for a demand density of approximately 100 parcels/km², truck-launched delivery drones could be useful in reducing total operations costs by nearly 25% in a large and low-density service area. GADDs exhibited greater economic potential than truck-launched delivery drones in densely populated areas. Utilizing GADDs would result in a 60% decrease in total operation costs (compared to business as usual) for a total demand density of 300 parcels/km². GADDs appeared to be the most effective option for reducing externalities.

Dukkanci et al. [97] developed the Energy Minimizing and Range Constrained Drone Delivery Problem (ERDDP). The concept behind the problem was that drones were used to deliver goods to various customers, and the drones were carried via conventional vehicles which served as launch spots. The problem involved assigning customers to the launch points, choosing the launch points from a possible set of locations from where drones would be launched to provide service to customers, and determining the speed at which drones would travel from the customers to the launch spots. Drones could be released from a parking depot where they were carried by trucks, or they could take off from a central depot. In the latter case, one drone was carried by each truck to a prearranged parking spot, where it served only one customer before returning to the truck to be prepared for the next delivery. The researchers assumed that the drone's battery was used until it ran out; at that point, another battery was used to keep the delivery activities operating continuously while the empty battery was being recharged. The study's essential assumption was that drones could remain on route and maintain a predetermined speed the entire trip. The comprehensive computational results showed several managerial implications. For instance, optimal solutions with realistic computation durations could be found by solving the operational problem's second-order cone programming formulation. It's possible that the depot could not be the ideal spot for a drone to take off, even though using it as a launch spot doesn't cost anything for operating trucks. Another finding was that operators should constantly think of utilizing a more flexible deadline or launching many drones from the same spot as this would assist in lowering the drone's speed and hence lower costs.

By taking into account a massive European logistics provider (ELP), Coindreau et al. [98] provided a methodology for managing a parcel delivery problem employing a vehicle fleet equipped with drones. The ELP suggested utilizing a mixed fleet of vehicles, with drones integrated into trucks. The trucks' and the drivers' authorized had two primary tasks: delivering items to customers' locations and controlling (i.e., locating, moving, loading, recharging, and launching) the drones during their travel. The study emphasized on the static day-ahead scheduling of parcel deliveries, where the travel time for each delivery was predetermined. According to the results, trucks had a greater capacity but also incurred greater costs and traveled more slowly. Since the research assumed drones were faster and less expensive but their range and capacity were limited, the researchers named this situation MC-VRPTW-D, or

the multi-compartment vehicle routing problem with time windows and drones. The maximum working-day duration for the drivers and the drone's flight autonomy, which depends on the battery size, were considered. Driver wages, fuel consumption, and drone electricity consumption were the variable costs that were produced by the truck-and-drone fleet's delivery operations. For the MC-VRPTW-D, the researchers utilized a mixed-integer linear program (MILP). An adaptive large neighborhood search (ALNS) was developed to solve the MC-VRPTW-D using an insertion-based metaheuristic. The study proposed a modeling framework to decrease variable costs related to a specific fleet of trucks and drones, aiming to optimize the overall delivery costs, including both fixed and variable expenses. The findings emphasized the significant cost reductions that might be achieved by using drones to serve clients, as opposed to relying only on truck-based systems such as the traditional VRPTW. The cost savings varied between 20% to 35% for situations having 50 or 100 clients, if all customers were eligible to be served by drones. The findings also demonstrated that to compensate for the fixed costs of drone usage, a minimum percentage of customers must be accessible by drone. Fuel-related costs could be reduced by at least 15% when over 50% of customers were served by drone. When every customer was reached via drone, this reduction could exceed 50 percent.

2.1.3. Examining and comparing different transportation modes

Park et al. [99] evaluated the environmental effects of drones, motorcycles, and electric motorcycles with the life cycle assessment (LCA), which took into account the production, distribution, usage, disposal, and transportation of raw materials. In addition, actual delivery distances were used to examine the environmental improvement effects of drone usage in both urban and rural areas in the residential regions of Pyeongchang-gun, Gangwon-do, and Yangcheon-gu, Seoul. According to the results, while electric motorcycles produced more particulates because particulates are largely generated during electricity production, gasoline motorcycles had a higher greenhouse gas emissions factor since more greenhouse gases were released during the combustion stage of gasoline than during the manufacturing stage.

Gawron et al. [100] performed a life cycle assessment (LCA) for Connected and Automated Vehicle (CAV) sensing and computation subsystems integrated into Internal Combustion Engine Vehicle (ICEV) and Battery Electric Vehicle (BEV) platforms. In the study, the Life Cycle Assessment (LCA) assessed the environmental effects of Level 4 CAV subsystems used for driving and monitoring in specific use cases, without requiring human involvement. Only

direct implications of CAV technology adoption were considered. The direct effects included eco-driving, platooning, enhanced intersection connection, and higher interstate speeds. The life cycle stages included producing the materials, manufacturing and assembly, utilization, and end-of-life management. A comparison between non-CAVs versus Level 4 CAVs in the US under several scenarios over the near-to-medium future was performed. Platform vehicles were combined with CAV subsystems in three sizes (small, medium, and big) separately to generate six scenarios. The study concluded that ICEVs have a higher Greenhouse Gas Emission (GHG) burden and fuel consumption was more sensitive to increased mass, resulting in a CAV subsystem burden that is approximately two times lower for BEVs compared to ICEVs. CAVs with electric powertrains emitted 40% less GHG emissions over their lifetime compared to conventional powertrains. CAVs' operational effectiveness reduced fuel consumption by 14%, resulting in significant environmental advantages compared to the baseline scenario. The researchers also highlighted that when comparing GHG emissions at the subsystem level and changing the powertrain, a BEV was a better platform for CAV components than an ICEV in terms of minimizing environmental impact.

Figliozi [101] performed an analysis of drones, sidewalk autonomous delivery robots (SADR), road autonomous delivery robots (RADRs), electric cars (EV), and vehicles with internal combustion engines (ICE) to assess their efficiency in terms of vehicle miles, energy consumption, and CO₂ emissions. The findings indicated that in delivery conditions with low density and time constraints, drones proved to be more efficient, and regardless of what type of autonomous vehicle was utilized, there would almost certainly be a significant reduction in carbon emissions.

Ehrler et al. [102] were interested in finding out whether e-commerce would be relevant for groceries in Germany in the years ahead, as well as whether switching to electric vehicles for e-grocery sales in particular and online sales, in general, was a feasible alternative for logistics providers that would be sufficiently accepted to improve cities air quality in light of expected changes in consumer behavior. Based on real test instances, the possibilities and requirements for the use of electric vehicles in their distribution were analyzed. The literature existed and secondary sources on the German online grocery market provided the basis for the study. Various aspects of the primary subject were investigated using the available data. According to

the research, electric vehicles could lower local emissions on distribution in general and online grocery sales in particular. The study also highlighted that the utilization of renewable energy sources could contribute to enhancing the sustainability of urban delivery.

Raghunatha et al. [103] conducted a study to compare the efficiency of an electric truck, an e-truck, and a diesel truck by implementing environmental impact assessments, life cycle cost (LCC) assessments, and delivery time assessments for delivery scenarios to pick-up locations located mostly in rural areas between mid-size cities. The functional unit (FU) was selected as a single standard shipment with three stops and 250 packages, each weighing 2 kg, with a maximum total weight of 500 kg. For deliveries in rural areas, the results indicated that drones emit fewer emissions than diesel trucks. Furthermore, because of their high level of automation, the study proved that drones are a more affordable option than diesel and e-trucks. [The analysis suggested that the drone had the lowest LCC per FU of all routes, in contrast to the trucks, which had LCCs that were approximately equal. According to the analysis, the highest expense for both trucks was the staff. It implied that most of the drone's lower LCC could be attributed to staff cost savings. Therefore, owing to their adaptability as a form of air transportation, drones consistently proved to be the fastest choice.

To demonstrate the effects of the drone's range, Rodrigues et al. [104] performed a first-principles study and constructed an open model based on 188 delivery drone flights of a quadcopter drone M100 with a variety of payloads, speeds, and altitudes. The investigators also developed an energy model and a machine-learning algorithm to evaluate energy throughout takeoff, cruise, and landing. The study compared the drone's energy usage and greenhouse gas emissions with delivery vans, trucks, and electric cargo bicycles based on package and distance. The investigators achieved this via their energy model. The results were as follows: With normal operation parameters, a quadcopter's faster speed frequently enabled longer delivery ranges for the same amount of energy since the total time of flight decreased with increasing speed. Due to their small size, low weight, and limited payload capacity, small quadcopter drones offered some of the lowest overall energy consumption per distance of any other mode of transportation. When it comes to the consumption of energy for each package, small quadcopter drones and electric cargo bicycles ranked among the most energy-efficient methods to deliver tiny packages, presuming that the payload and space capacity of the first type could

accommodate all packages delivered by the other alternatives. Quadcopter drones and electric cargo bicycles were amongst the vehicles with the lowest CO₂e per kilometer, and they were a competitive alternative concerning GHG emissions per package, according to an analysis of the GHG emissions of the fuel used in each mode of transportation. Additionally, the investigators demonstrated how the drone's emissions vary by US location based on the type of electricity used.

Wygonik et al. [105] assessed the carbon dioxide (CO₂) emissions associated with using personal vehicles compared to shared vehicles for supermarket shopping. The study examined the importance of modeling routing and scheduling logistics and analyzed if the results of an American case study were consistent with those of European case studies. The researchers additionally investigated the potential reductions in CO₂ emissions for both of these bounding scenarios: random customer selection and location-based assignment. The emissions factors for personal vehicles that operate on gasoline indicated personal travel. A random sampling of the service area's households was utilized to estimate customer-directed service. For short-haul diesel-fueled single-unit trucks, the delivery vehicle travel used emissions factors in the study. As a result, a household's one round trip to the nearest grocery store could potentially be replaced by delivery from that location.

Li and Kunze [106] compared UAVs with SUGVs for urban parcel delivery, examining practical, conceptual, technological, commercial, and environmental aspects. The researchers developed a parameter-based cost calculus model to estimate the cost per shipment for each technology. To determine the cost per shipment of drone delivery, a cost calculus template that considered both capital and operating costs was introduced. The researchers also proposed a framework for calculating the cost per shipment (CPS) and cost per payload unit (CPP) for UAV and SUGV delivery. When calculating these costs, the researchers made the assumption that the unmanned vehicle loads at a mini-hub and makes straight, non-stop deliveries of one good from each shipment to every customer. The findings revealed that, from a practical point of view, these technologies were on the edge of shifting from a test environment to commercial use, primarily in parcel and grocery delivery and medical supplies distribution. The study also revealed that the CO₂ footprint of both types of drones was significantly affected by the electricity generation technology. As a result, the researchers considered the average cruising

speed, beeline service, drone lifetime in mileage, drones per operator, and beeline distance correction factor to be important cost-causing factors for drone delivery. On the other hand, the researchers considered the average battery lifetime in miles, drone purchase price, and operator hourly costs to be slightly important cost-causing factors for drone delivery. The shipping loading and unloading time, cost of energy per KWh, energy consumption rate, and battery cost were not considered to be cost drivers.

Ma et. al. [107] focused on the effects of three key factors for two sample markets: the UK and California. Comparison of like-for-like vehicles (Battery Electric Vehicles (BEVs) versus Internal Combustion Vehicles (ICVs)), the impact of real-world driving circumstances, and the inclusion of Greenhouse Gas (GHG) Emissions related to the manufacturing of the vehicle, disposal, etc. as well as the additional energy needed for charging the batteries by GHG Life Cycle Assessment (LCA). Initially, the Tank-to-Wheels (TtW) study was examined. In the study, TtW referred to the vehicle in-use phase of the LCA and compared (as closely as possible) identical vehicles using a driving simulation. A comparative analysis of the state-of-the-art efficient ICVs was conducted with Hybrid Electric Vehicles (HEVs). The requirement to accurately allocate the relevant GHG intensity to the electricity utilized to charge the BEVs' batteries was the second problem that was taken into account. The third factor was the greenhouse gas emissions related to the lifecycle of the vehicle, which were excluded from conventional "Well-to-Wheels" (WtW) assessments. The primary goal of the system under analysis was to enable a vehicle to transport a specific load—passengers or cargo—for the duration of its life, which is estimated to be 15 years. Therefore, per vehicle kilometer traveled was the functional unit employed in this research. The study comprised carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O) gasses in addition to refrigerant used in vehicle air conditioning (A/C). In the UK, in urban driving conditions with modest passenger and accessory loads, the BEV outperformed the ICV in terms of WtW and total lifetime (fuel and vehicle) GHG emissions for mid-size passenger vehicles. When compared to ICVs, BEVs could save a lot of greenhouse gas emissions as long as the grid's greenhouse gas intensity during battery charging is acceptably low. Since the greenhouse gas emissions are related to the production of batteries, BEVs had greater vehicle life cycle emissions than ICVs. These emissions are related to vehicle manufacturing, disposal, etc.

Satiennam et al. [108] evaluated the decrease in CO₂ emissions from Thailand's transportation sector and surveyed motorcyclists to find out what percentage of them would be willing to utilize an electric motorcycle. Before conducting individual interviews with the sample, participants were informed about the advantages and disadvantages of the characteristics found in the current market for electric motorcycles. The study additionally assessed the decrease in CO₂ emissions that was caused by cyclists switching to electric motorcycles. The transport demand forecasting model created by a prior study was used to calculate the volume and average velocity of the traffic throughout the road network. On each road link, the CO₂ emissions by the type of vehicle were also calculated. The transport demand forecasting model created by a prior study was used to calculate the traffic conditions, including volume and average velocity, along the road network. On each road link, the CO₂ emissions by the type of vehicle were also calculated. When electric motorcycles were made available to riders, CO₂ emissions would drop by 2.4% compared to the state of doing nothing, according to the study. Additionally, the investigators stated that in order to increase the acceptance of electric motorcycles, the current commercial models need to be created and manufactured to satisfy the needs of riders, such as raising manufacturing standards, boosting maximum speed and travel distance, and having a more appealing design.

Nocerino et al. [109] presented the findings from the Italian Pro-E-Bike pilot program, which is founded by the Intelligent Energy Europe program, and encourages the use of clean and energy-efficient vehicles. The research explored the potential of electric scooters, bicycles, and light electric vehicles (LEVs) as alternatives to combustion engine vehicles for delivering goods and providing services in urban areas. Over a period of 3 to 12 months, 39 pilot firms tested 74 electric vehicles, which delivered small goods and letters, meals, and fruits, or offered waste collection or home care services. The switch from conventional to light-duty vehicles (LEV) had noticeable results concerning CO₂ emissions. Using an LEV means reducing between 45 and 370 g of CO₂ each km. This resulted in CO₂ emissions of 18,584 kg that were saved totally all through the pilots, which means that from 1.7 to 21.0 kg of CO₂ could be saved daily by each e-vehicle. In addition, every e-vehicle used in the trial has energy cost savings ranging from 0.9 to 11.0 €/day.

Hao et al. [110] investigated whether or not electric vehicles with batteries assist in reducing GHG emissions in the context of China by looking at the lifecycle costs and GHG emissions of conventional vehicles, hybrid electric vehicles, and battery electric vehicles, and comparing their cost-effectiveness for reducing GHG emissions. The study compared the following vehicle technologies: conventional gasoline vehicles, heavy hybrid electric vehicles (HHVs), mild hybrid vehicles (MHVs), and electric vehicles with 100, 200, and 300 km of range (EV100, EV200, and EV300). The standard vehicle was determined to be a gasoline-powered vehicle. Fuels and greenhouse gas emissions from the manufacturing of vehicles were both taken into account. The vehicle's life cycle began from manufacture and ended when it was no longer in use. The fuel's boundary was the point at which it was acquired and burned. According to the study, BEVs could lower life-cycle greenhouse gas emissions in China. The study additionally included a single-factor analysis. Coal power share, coal power efficiency, battery-specific energy, battery learning rate, the intensity of vehicle usage, and gasoline price are among the influencing factors. According to the findings, the two factors that most affect how cost-effective BEVs are the price of gasoline and the battery learning rate.

Ou et. al. [111] examined the greenhouse gas (GHG) emissions of coal-to-liquid (CTL) fuels and electric vehicles (EVs) powered by coal-to-electricity and petroleum-based fuels utilized by identical platform vehicles in China. Vehicle cycle and battery manufacturing emissions, and entire fuel cycle and use-phase emissions were all taken into account using a life cycle assessment (LCA) model. The model covered extraction and transportation, the production of vehicles and their parts, and the recycling and disposal of vehicles. In order to calculate the global warming potentials for CO₂ emissions, the three main types of GHG emissions (CO₂, CH₄, and N₂O) were taken into account. A 100-year time horizon was assumed in the calculations. The results proved that even if coal is used to generate or transport the fuel, EVs appear to be a promising solution for reducing GHG emissions. When compared to petroleum-based gasoline vehicles and diesel-fueled hybrid electric vehicles (HEVs), coal-power charged EVs could reduce life cycle greenhouse gas emissions by approximately 60 to 70% and 40–55%, respectively, at maximum rates for Coast Clutch Solenoid (CCS) collection. If EVs were used instead of petroleum-based fuel in traditional internal combustion engine vehicles (ICEVs), life cycle greenhouse gas emissions could be reduced by 3–36%, even in the case of coal electricity utilized without CCS. The battery life cycle, which includes battery

manufacturing, disposal, and recycling, contributes approximately 5% of the greenhouse gas emissions for coal-power charged electric vehicles (EVs), while the ICEV cycle, which includes material production, parts manufacturing, vehicle assembling, disposal, and recycling, ranked in second place (about 20%). On the other hand, CTL fuels were anticipated to result in higher greenhouse gas emissions from transportation fuels. EVs were superior to CTL fuels in terms of assisting in achieving the dual objectives of decreasing greenhouse gas emissions and enhancing energy safety in the passenger transportation sector.

With a focus on e-commerce, Patella et al. [112] conducted a comprehensive review of the literature on research examining the utilization of electric vehicles (EVs), autonomous vehicles (AVs), and drones in urban logistics. The review contained 159 papers that were ultimately selected for inclusion. The review revealed three primary categories: sustainability (S), policy (P), and optimization and scheduling (O). The distribution of the works in category was shown by the results: 42% of the works were in the optimization and scheduling group (O), 34% were policy-related (P), and 24% were sustainability-focused (S). 11% of the articles had references to e-commerce, with the policy group accounting for 5% of those references. According to the study, there had been a significant increase in academic interest in urban freight distribution from an operation research perspective in years. In addition, the researchers highlighted that several studies had proposed models for the green vehicle routing problems (GVRSPs) which consider a fleet that consists of both AVs and traditional manually controlled vehicles. In terms of all CO₂ emissions related to e-commerce, the last mile delivery accounted for 32% of the emissions on average. The researchers mentioned that, from a sustainability perspective, the utilization of renewable energy generation could further increase the competitiveness of green vehicles in last-mile logistics. The findings also revealed that the assurance of short delivery windows in e-commerce could cause more pressure on the system, decreasing the likelihood of demand aggregation and the degree of freight vehicle consolidation.

Through a systematic literature research, Oliveira et al. [113] determined the primary vehicle types described in the literature that could potentially be utilized in the last mile of urban freight distribution, hence increasing the operation's sustainability. To expand the scope of papers included in the review process, the databases Web of Science, SCOPUS, Science Direct, DOAJ, and Compendex were utilized for identification purposes. In the results, the researchers showed

the distribution of the papers assessed by the scientific journals in which they were published. The researchers additionally provided an illustration of the year that every study in this systematic literature review was published. According to scientific research, a more efficient and environmentally friendly alternative to last-mile delivery in cities was to reduce the size and capacity of the vehicles used. Of all the papers reviewed and examined, 42% suggested bicycles or tricycles as a suitable alternative for last-mile urban delivery. Of the studies that examined energy use, 36% pointed to human propulsion and 64% to electric energy. Furthermore, the systematic literature review's findings highlighted the potential application of electric vehicles as a sustainable and efficient alternative for last-mile distribution in urban freight transportation. 69% of the papers highlighted the transition from fossil fuels to electric energy in vehicle propulsion.

The main objective of Edirimanne et al.'s [114] vehicle routing problem (VRP) model was to minimize distance traveled during food delivery operations by including practical constraints including payload capacity and maximum flying range. Three delivery options, including delivery by UAV, were compared with the aim of evaluating each method's feasibility and determining which is the most efficient. There were three different ways that customers could order pizza: over the phone, via the official website, or in person at an actual restaurant. The study's scenario comparison investigated three scenarios to determine whether combining VRP and UAVs in food delivery logistics is feasible. In these scenarios, the best and most efficient routes were identified utilizing the VRP model, and each route and dataset was evaluated in terms of total distance, time, cost, and CO₂ emissions. Depending on the energy source of the vehicle, two techniques were used to calculate CO₂ emissions for motorcycles and unmanned aerial vehicles. The motorcycle's fuel efficiency and the amount of CO₂ emitted per liter of gasoline burned during the trip were taken into account when calculating the CO₂ emissions generated by the motorcycle. The CO₂ emission per km from UAVs throughout the delivery was calculated using the CO₂ emission during the electricity production process in kilos per kilowatt hour. The travel cost analysis for each mode of transportation only considered the operational fuel and energy costs. Significant savings were observed in four important areas when comparing the modified motorbike delivery system with VRP: total travel distance, cost, and CO₂ emissions, along with a reduction in duration of travel. Furthermore, the UAV system demonstrated a considerable decrease in distance traveled, length of time traveling, cost, and

CO₂ emissions compared to the VRP-implemented motorcycle system, confirming the premise of the first research aim. On the other hand, the cost per package decreased by 17% using the VRP-implemented motorcycle delivery system and by 28% utilizing the VRP-implemented UAV delivery system. In conclusion, the VRP-implemented UAV delivery system proved to be the most effective option for food delivery among the three systems.

Melo and Baptista's [115] study examined the impact of switching from vans to cargo bikes by taking into consideration the interests of both the public and private organizations through a case study conducted in the Portugal. There was also discussion of changes in running costs, energy consumption, CO₂ emissions, and travel distance. Mobility, dependability, and operational efficiency indicators had been measured thanks to the tracking of traffic key performance indicators, well-to-wheel energy and CO₂ emission savings, and other factors. In order to conduct this study, a tiny traffic simulation model was developed in the Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUN). In this microscopic traffic simulation, occurrences that cause congestion—like illegal double-lane parking—were also simulated. Information on the physical features of the infrastructure, vehicle dynamics, traffic volumes (considering the flows from surveys), traffic signal timing, and incidents comprised the input data for AIMSUN. Initially, the base scenario was constructed using this data, and this assisted in confirming the model that had been developed. Following that, for the purpose of investigating the consequences of various market shares on the mobility of the study field, a number of scenarios relating to the introduction of electric cargo bikes in place of traditional vans were assessed and examined. The study field consisted of 321 sections, 158 nodes, and a total of 26 km of road network extension (the sum of the section extensions). Calibration and validation were the two stages in the model generation process. Driver behavior parameters were the main emphasis of the first stage, whereas traffic volumes, travel times, and speed profiles were the subject of the second. The key result indicated that cargo bikes had the potential to substitute up to 10% of traditional vans in fields with a maximum linear distance of roughly 2 km, keeping the same level of network efficiency throughout. The findings revealed that using electric cargo bikes to replace 3, 5, or even 10% of the study area's freight movements could improve traffic performance. Also, it was possible to reduce the WTW CO₂ emission impacts of urban logistics by up to 73%, or 746 kg of prevented emissions. Electric cargo bikes also had positive impacts on all vehicle types and

circumstances when used in urban logistics activities, with up to 25% reductions in external costs. In summary, cargo bikes could serve as an environmentally friendly urban logistics solution when integrated into the city at the right spatial scale.

For the purpose of assisting people in disadvantaged regions overcome the problem of food desert, Choi et al. [116] investigated affordable delivery options. Five different delivery networks were taken into consideration: parcel lockers, personal automobile deliveries, electric cargo bikes, traditional trucks, and personalized ride (PR) transportation services. The delivery trucks visited each customer in the service region, or demand point, with the objective of the study. The researchers made the assumption that trucks were capable of carrying up to 250 parcels, however, they might not constantly do so. On the other hand, because of the e-bike's 150–300 kg payload capacity, it generated a lot of fulfillment trips to the depot. Thus, the researchers employed stationed trucks in place at the depot. As a result, whereas e-bikes are exclusively used for last-mile deliveries, bikes resupplied packages from trucks. Deliveries performed by drivers using their cars to third parties followed the same process and had the same features as deliveries performed by trucks. The PR delivery alternative took into account a car picking up customers in a service region and driving them to the closest grocery shop, rather than delivering goods to them. Truck drivers delivered all of the goods in lockers in the parcel locker delivery case. After that, in order to obtain their belongings, customers must go to the pickup places. The cost function's components were assigned selectively to each delivery option when calculating the cost functions. In the study, the total number of goods (or passengers for personalized ride services) that a vehicle could carry could not exceed the maximum capacity of the vehicle due to system boundaries. After all the calculations, optimized outputs for the different options were compared with the total cost. The findings indicated that home delivery services were less expensive than personalized ride services and parcel locker delivery. The least expensive method to distribute fresh goods was through personal car deliveries made by third parties, according to the numerical data. On the other hand, the cost of parcel locker delivery and personalized ride service was higher compared to the cost of home delivery services.

Chen and Wang [117] investigated the most suitable options for ordering and transportation modes under various carbon emission reduction strategies by using stochastic customer demand

to study the retailer's ordering and mode selection problem. The impact of environmental performance and the inclusion of reduction of carbon emissions target in transportation and ordering decisions on the logistics and supply chain system's risk were also investigated. A one-period, two-echelon supply chain composed of a supplier and a retailer had been taken into consideration in the study. Also, the supplier produced products with a short shelf life. With a stochastic demand, the retailer placed orders with the supplier and sold to final customers. The study investigated how the retailer's optimal solutions, profit, and total carbon emissions are affected by two different carbon reduction policies: cap and trade and carbon emission cap. The researchers aimed to comprehend the impact of different carbon reduction strategies and the objective of reducing carbon emissions on the risk of the logistics and supply chain system by comparing the supply and demand risks in three distinct scenarios. The findings demonstrated that the emission cap policy had two major transportation mode changing thresholds. The retailer would choose the less expensive method of transportation with higher carbon emissions if the government's initial carbon emission quota exceeds the first threshold. Firms would choose the more costly, low-carbon-emission method of transportation if the quota is lower than the second threshold. Under the cap and-trade strategy, in contrast to the cap policy, this threshold was unaffected by the initial government carbon emissions quota. If the threshold be exceeded by the unit price of carbon emission trading with the external market, the store would choose the more expensive transportation option that produces less carbon emissions. In contrast, the retailer would shift to a less expensive option which has higher carbon emissions if the unit price of carbon emission trading is less than the threshold. The authors also emphasized that the research suggested that integrating the carbon emission reduction goal into the decision-making process when selecting a mode of transportation and placing orders could effectively mitigate environmental risks associated with various carbon emission reduction strategies.

Delucchi et al. [118] comprehensively addressed various aspects of electric vehicles (EVs), the infrastructure required for their improvement, their impact on greenhouse gas (GHG) emissions, the use of materials and petroleum, lifecycle costs, consumer acceptability, and regulatory concerns. According the findings, with the right circumstances, EVs running on renewable fuels could even have extremely low or zero GHG emissions. Battery EVs, plug-in hybrid EVs, and hydrogen fuel cell vehicles have greater beginning costs, lower fuel costs,

reduced external costs, potentially higher insurance costs, and potentially cheaper maintenance and repair costs as compared to conventional gasoline vehicles.

Siragusa et al. [119] examined the competitiveness of electric vehicles (EVs) and internal combustion engines (ICEVs) for last-mile delivery in business-to-consumer (B2C) e-commerce, taking into consideration both environmental and economic factors. As a measure of the fuel produced, the fuel burned during usage of the vehicle, and the manufacture and disposal of the vehicle, GHG emissions were chosen. The life cycle assessment method was utilized to evaluate the environmental impact. Based on a total cost of ownership (TCO) analysis, the economic evaluation provided a comparison between the two vehicle types over a period of ownership. The algorithm that calculates the total cost of ownership (TCO) requires three distinct inputs: (i) travel data (kilometers driven annually), (ii) vehicle data (power, fuel, or electricity consumption, depreciation rate), and (iii) cost data (fuel or electricity price, road toll). Particularly, 260 days a year were considered, and the three leading Italian express courier services were contacted to determine an average daily travel distance of 80 km. The emissions from the generation of fuel or electricity were referred to as energy production. This process refers to fuel and includes its distribution, transportation, refinement, and extraction. For electricity, the emissions related to its production includes its generation, transmission, and distribution (taking into account the country's electricity mix). Vehicle-related greenhouse gas emissions were referred to as energy consumption. As a result, EVs in Milan were a competitive substitute for ICEVs when taking into account the annual mileage assumed by the study. Compared to ICEVs, EVs have fuel costs that are about 60% less in terms of total energy. Considering an 8-year vehicle lifespan, EVs emitted almost half of the greenhouse gas as ICEVs. When taking into account the local emissions caused by an ICEV's diesel usage, shifting to an EV could result in an annual CO₂e reduction of 2,7 tonnes. When an eight-year time frame was taken into account, the usage of EVs for last-mile delivery proved to be economically feasible.

In order to determine the most effective travel mode for last-mile delivery, Zhao et al.'s [120] study suggested a hybrid approach that combines data mining with multiple attribute decision-making. The study utilized a big data approach to determine the weights of composite criteria, consisting of journey time, travel cost, and carbon emissions, for last-mile travel-mode decision

making. Walking, bike sharing, buses, and on-demand ride-sharing services (RSS) were the last-mile transportation options that were taken into consideration throughout the selection process. Referred to as the entire quantity of carbon dioxide that has the potential to cause global warming, direct greenhouse gas emissions were used to determine the environmental performance of last-mile travel. Walking and bike sharing have no direct connection to the combustion of fossil fuels, hence in this study, their direct carbon emissions were equal to 0. Through the use of the keyword frequency, weights for each criteria were determined. Using Sina Weibo, data mining was performed with the four travel types specified as keywords. The word frequency was utilized as the index weight, and keywords with the first 1000 frequencies were chosen. Four different transport modes and various combinations of them were ranked utilizing the suggested method, and the last-mile travel distances of 1, 2, 3, 4, or 5 km were taken into consideration in five different scenarios. Bike sharing comes in front when the travel distance is 1 or 2 km. Considering carbon emissions during usage, it also had an incomparable advantage over the bus and RSS. The disadvantage of the speed of bike-sharing (in comparison to the bus and RSS) became more apparent as the travel distance increased to 4 or 5 kilometers. The RSS is more expensive in terms of the monetary cost than the bus even though its speed is higher. Furthermore, compared to the RSS, the bus had lower direct carbon emissions per person and was capable of carrying a larger number of people. As a result, the investigators discovered that the most suitable mode of transportation significantly differs depending on the last-mile distance.

Boysen et al. [121] conducted a survey of last-mile concepts, with a particular focus on the decision-making problems that arise during the setup and operation of each concept. Alternative last-mile concepts were addressed in the survey. These concepts were defined as particular process chains that employ one or more vehicles (such as a delivery van and/or a drone), storage facilities (such as a central depot and/or a postal locker), and handover options (such as customer self-service or attended home delivery) to complete the last-mile delivery task. The survey had been divided into three separate groups: ideas that were already in usage at that time, ideas for the immediate future where the required technology was undergoing assessment, and ideas for the far future where important technological elements were still being developed. For each last mile concept that fell into one of these categories, the decision problems were the setup (or design) of infrastructure (e.g., location and capacity planning of storage facilities),

the staffing and fleet sizing (e.g., workforce planning of delivery persons and fleet sizing of delivery vans), and the routing and scheduling (e.g., scheduling drone launches from trucks). There was also a tabular summary of the research on last-mile terms in the results. A list of articles about the last-mile delivery terms covered in the study was also provided by using suitable acronyms used in the overview in the methods of problem type and solution approach. The findings indicated that current last-mile research focuses primarily on routing but future studies ought to focus on several more significant decision-making areas. For instance, for non-traditional delivery methods, time window management and the problem of ways to determine appropriate delivery time windows for customers have not yet been addressed. The results also showed that any paper which is addressing a particular last-mile delivery concept's decision problem is comparing their approach to an alternative delivery option. It was emphasized that these benchmark tests are insufficient for systematic comparison of all new and conventional delivery concepts so a unique data set derived from publicly available real-life data is required.

2.2. Determining Negative Environmental Effects of Other Various Factors

Fan et al. [122] calculated pollution emissions like heavy metals to air, inorganic emissions to air, etc. from the production and distribution processes of express packaging materials (package boxes, plastic bags, woven bags, envelopes, and tape) based on data from Gabi 6.0 regarding the types and amounts of packaging materials used by China's express delivery sector in 2015. Utilizing the weight as a distribution criterion and the percentage of China's energy generation, this article apportioned various ecological emissions to the express packaging materials. The entire express delivery service and the ground distribution operations belonging to 2015 defined the functional unit. Based on production and consumption processes, package boxes had the greatest CO₂ emissions out of the six types of packaging materials, according to the study.

A stochastic model was developed by Shahmohammadi et al. [123] in order to measure the changeability of the (GHG) footprints related to the distribution of products and purchasing of fast-moving consumer goods (FMCGs) via traditional retail (brick and mortar), online retail and delivery from a store-based supplier (bricks and clicks), and online retail and home parcel delivery from a non-store-based supplier (pure player). The variability was propagated throughout the supply chain using a Monte Carlo simulation. The researchers also investigated how consumer decisions and behaviors affected the usage of electric cargo bikes for pure players' last-mile footprints. The findings showed significant differences between the GHG footprints of pure players and brick and mortar when vehicles are utilized for purchasing. The

two main factors influencing the variation in the GHG footprints of the three retail channels were the number of products purchased and the travel distance of the last mile. The study also found that by shifting from delivery vans to electric cargo bikes, parcel transportation could decrease greenhouse gas emissions approximately 26% so the researchers emphasized that shifting to delivery vehicles to electric cargo bikes, pure players could lower their last-mile footprints while also decreasing the failure rate of deliveries.

Van Loon et al. [124] aimed to identify which criteria are most important for assessing the environmental sustainability of various fulfillment channels, and a Life Cycle Analysis (LCA) model was developed to compare the environmental impact of various fulfilling methods. In addition to the traditional brick and mortar retail channel for fast-moving consumer goods, the methodology was applied to the most commonly used Business to Consumer (B2C) e-commerce models in the UK. The model accounted for all impacts associated with the movement and storage of products from the production to the consumer (and back again in the event of a return). Modeled data for producer and retailer transportation (excluding last-mile delivery) covered truck operations using several fuel types (diesel, biofuel, natural gas, and hybrid). Utility consumption (electricity, fuel, gas, and water) for various buildings in the modules (manufacturer and retailer distribution centers, e-fulfillment center, grocery, etc.) was also included. Furthermore, for last-mile packaging, cardboard boxes, filler materials, and plastic bags were used. The study found that e-commerce's environmental sustainability is strongly affected by consumer travel behaviors, e-fulfillment methods, and basket size. The importance role of basket size for deciding the optimal distribution channel was also proved. Emissions per item increased in inverse proportion to basket size, regardless of fulfillment method. The researchers highlighted that the amount and type of packaging, as well as the energy efficiency of grocery and e-fulfillment center activities, are important contributors to climate change. The average quantity of products purchased, as well as the carbon footprint of van home deliveries and consumer pick-up methods, results in much higher carbon footprints.

Wang et al. [125] conducted a study in the UK that compares the environmental consequences of supermarket grocery retail shopping and an online recipe box delivery model. The study also analyzed the environmental impact of sustainability-oriented innovations (SOIs) on the processes associated with food consumption and resulting food waste. Red meat, poultry, fish,

vegetarian, and vegan products were among the key ingredients used in the five meals, which were obtained from the grocery store and an online recipe box delivery service. The study highlighted carbon emission hotspots along the entire food supply chain using the life cycle assessment (LCA) approach. Even if additional environmental factors including eutrophication, acidification, land usage, and water use were also calculated in LCA. The comparative analysis revealed that all five of the recipe box meals have 10.8% less carbon emissions overall than the equivalent meals obtained from a supermarket. Additionally, the researchers compared the differences in overall carbon emissions between the online supermarket grocery delivery service model and the online recipe box service model. According to the study, when the online delivery service takes the place of the supermarket retail operation, the differences in total carbon emissions between the two food provision services are narrow for chicken, beef, and fish, even though the recipe box service generated fewer total carbon emissions than the equivalent meals obtained by the online delivery service.

Atilgan and Azapagic [126] analyzed the environmental impacts throughout the life cycle of fossil fuel power plants in Turkey, using 2010 as the foundational year. The study considered Turkey's 187 gas power facilities, 8 hard coal, and 16 lignite power plants. The generation from fossil fuels, particularly gas, hard coal, and lignite, was the focus. Life cycle assessment (LCA), which was conducted utilizing GEMIS 4.8 and GaBi v.6, had been used to determine the impacts. The study included the extraction, processing, and transportation of fuels, as well as the combustion of them to produce electricity in power facilities and the building and decommissioning of those facilities at the end of their useful lifespans. Turkish Ministry of Energy and Natural Resources (MENR), Turkish Petroleum Pipeline Corporation (BOTAS), Turkish Electricity Generation Corporation (EUAS), Turkish Electricity Transmission Company (TEIAS), and Energy Market Regulatory Authority (EMRA) were the primary sources of data. Various factors were taken into consideration: ozone layer depletion potential (ODP), photochemical ozone creation potential (POCP), abiotic depletion potential (ADP elements and fossil), freshwater aquatic ecotoxicity potential (FAETP), global warming potential (GWP), and human toxicity potential (HTTP), etc. The study found that gas-generated power has the lowest environmental impact per KWh, except for ODP. Overall, lignite is the most harmful option. The majority of effects stem from power plant operations and fuel transportation. The majority of GWP for all three alternatives originates from fuel combustion,

with lignite accounting for 97%, hard coal accounting for 83%, and gas accounted for 74%. CO₂ emissions made up 98% of the overall GWP for lignite and approximately 90% for hard coal and gas generation. Annually, generating energy from fossil fuels emits 109 Mt CO_{2e}., mainly through lignite and hard coal power.

Gevaers et al. [127] established a last-mile typology to simulate the total last-mile costs. The purpose of the study was to acquire an understanding of the cost effects caused by changes in characteristics (cost drivers) of last-mile transportation in urban areas, primarily economic but also environmental aspects. The current stage included developing a last mile costs model that could simulate the B2C last mile costs per unit delivered. These costs were computed from the time the parcel or product was transported (from the last delivery point (DC) of the logistics service provider or the shippers) until it was delivered to the customer's house or a designated pickup location. An internal standard shipping cost was always the starting point. Data from expert interviews as well as literature were used to build this cost model. A total of 5 scenarios were considered, including the Base scenario. Regarding to results, it was acknowledged that modifications to last mile (sub-) characteristics have the potential to result in noteworthy financial effects in the last mile. For instance, modeling the difference in cost between a last-mile delivery in a densely populated urban area and one in a rural or averagely populated area offers a potential 5 EUR cost difference. In comparison to standard deliveries in rural areas, time window deliveries in urban areas could be less expensive. The significance of the high first-time hit rate (FTHR) in B2C delivery routes was also demonstrated by the simulation results, which implies the actual number of stops that are successful (effective) would fall below the average number of stops.

2.3. Identifying Customer Behaviors, Tendencies, and Preferences in Green Transportation and Green Brand Image

Mathew et al. [128] studied consumer perceptions of risk and green image within the framework of drone food delivery in India. Additionally, the researchers examined how functional, hedonic, cognitive, and social motivations affected consumers' choice of intent and innovative behavior using motivated consumer innovativeness (MCI). The study employed partial least squares analysis and structural equation modeling to analyze the data from the questionnaire survey. The data showed that customers are willing to ignore the early failures of this development and are not as concerned about the performance and delivery risk connected with

this novel technology. The results also indicated that consumers' behavioral intentions are positively influenced by green image, as addressing consumers' environmental needs frequently leads to the use of eco-friendly services like drones.

Hwang et al. [129] examined how demographics and previous experiences with environmentally friendly drone food delivery services affect behavioral intentions, including intention to use, word-of-mouth, and willingness to pay more. The data was gathered from 422 potential customers of eco-friendly drone food delivery services in South Korea. Every item was graded on a Likert scale, ranging from strongly disagree to strongly agree. 209 participants were men (47.9%), while 227 were women (52.1%). The majority of respondents were in their 30s (33.3%), followed by those in their 40s (26.1%). The most of those surveyed reported a high level of education, with 63.8% having a bachelor's degree. The study found significant variations in willingness to pay more based on gender, marital status, monthly income, knowledge of drone delivery services, and personal experience with drones. There were important disparities in word-of-mouth depending on age and monthly income, as well as distinctions in intentions to utilize based on marital status and previous knowledge of drone delivery services.

Merkert et al.'s [130] research aimed to determine consumer preferences for novel last-mile delivery, notably unmanned aerial delivery drones, in comparison to traditional postal delivery (postie) and the recent growth of parcel lockers across Australia. The study also examined the competition preferences and readiness to pay for key parcel delivery attributes (mode, speed, method, and time window), the role of contextual moderators such package value and security, and possible opportunities for logistics service providers in the rising e-commerce sector. A survey with stated choice experiments was conducted among 709 individuals in urban Australia. The researchers estimated panel error component logit models, determined consumer priorities, and ran 576 Monte Carlo simulations to predict potential delivery mode market shares. According to the findings, if there is no safe place to drop a parcel at a residence, both drone and postie become less appealing when compared to parcel lockers, highlighting the importance of situational context and infrastructure at the receiving end of last-mile delivery.

Namkung and Jang's [131] study used hypothetical scenarios to investigate customers' willingness to pay extra for eco-friendly restaurant activities. The researches argued four hypotheses which consider willingness to pay more for green restaurant activities is influenced by age, gender, income, and education. The researches additionally examined the impact of previous experiences, self-perception, and involvement (i.e. the degree of psychological connection between a person and the stimulus object). 334 valid responses were gathered via the online survey provided by an internet-based marketing research company in the US and used for analysis. According to the survey, 68.3% of customers at restaurants indicated that they would be willing to pay more for green restaurant activities. Furthermore, about one-fourth of those surveyed (26.3%) said they would be willing to pay more than 10% to eat at green restaurants. In addition, customers who were very likely to pay extra for green activities had a higher perceived green image than those who were not as likely to do likewise. The findings confirmed that consumers' perceptions of restaurants' green activities differ depending on how willing they're willing to pay extra. The findings also pointed out that the core green group is younger and has earlier experience dining at green restaurants, which contributes to their willingness to pay extra for a green brand image.

Serrano-Hernandez et al. [132] examined the present state of freight logistics in Spain and suggested alternative green routes and modes of transportation for the last mile of the city center distribution according to numerous variables that citizens had assessed. Using the preferences of the citizens who are particularly affected by transportation-associated problems in the city center, the researchers developed an analytic hierarchy process (AHP). Drones, electric vans and trucks, and traditional and electric-engine bicycles or tricycles are examples of these alternate modes of transportation in this study. The significance of each option while considering every criterion at the same time was indicated. Sustainability dimensions were included as the global criteria in a multicriteria model to analyze the options. The criteria were social, environmental, and economic. The researchers analyzed 107 observations in total. The researchers also established a beginning point (A) and a destination point (B) in the city center where two potential paths (Crossing the Pamplona City Center and Surrounding the Pamplona City Center) could be used in relation to the route alternatives. These paths varied based on the mode of transportation. With regard to the study, the respondents placed the highest emphasis on social criteria, placing the lowest weight on economic criteria. The most significant

subcriteria within the environmental and economic criteria, respectively, were air pollution and shipping costs. The findings also demonstrated that the drone performs more effectively than all of the other modes of transportation when analyzing the modes based on the criteria. The drone option specifically won in the following sub-criteria: visual impact, air and noise pollution, pedestrian safety, road use, delivery time, and life quality. The overall priority vector made apparent that using a drone is the most favored option for transportation, followed by cargo bicycles and traditional vans. For trucks and drones, avoiding the city center is preferable. Contrary to this, individuals choose to use cargo bikes to cross the city center.

2.4. Literature Review and Original Contributions

The literature frequently contains studies that compare traditional internal combustion engine vehicles (ICEVs) with electric-powered vehicles, as well as studies that compare the combined use of multiple vehicles (hybrid use) with other transport vehicles or with each individual vehicle type. The comparisons also considered factors such as vehicle capacity, vehicle ranges, and speeds. Also, there are studies in which the environmental impacts of the whole life cycle of the vehicles and the whole life cycle costs were determined. In addition to environmental and cost comparisons of vehicles, there are studies that compare these cases from different aspects, such as traditional shopping methods and online shopping methods. However, there isn't any study in the literature that offers substitute methods for the company's vehicles that use actual data and take into account both the orders' and the vehicles' characteristics. Furthermore, there haven't been any studies that used a simulation-optimization model to compare the delivery costs and environmental impact of each vehicle. By employing the methodology utilized in this study, it will be feasible to acquire real-life data and optimize it to provide more accurate outcomes. In the literature, no study has been identified that integrates simulation model-based MCDM models for vehicle fleet determination. This study's contributions to the literature are: i) determining the vehicle fleet based on the simulation optimization model; and ii) using the MCDM approach to select the most suitable vehicle fleet, taking into account the criteria associated with the problem in addition to the findings obtained from the simulation optimization model.

3. MATERIAL AND METHOD

3.1. Materials

The data in the application of the study was provided from a company serving in the fast food sector. According to 2023's data, there are 236,298 residents living in the area where the company's branch under consideration is located [133].

Within the scope of this study, datas obtained from the company are:

- i) order times (the time when orders are placed through the application),
- ii) the content of the orders (how many of which products are ordered),
- iii) the location of the orders (the address given by the customers for the delivery of the order),
- iv) the type of vehicle used for the transportation of the orders.

3.1.1. Calculation of parameters

i. Distances between locations

The main input needed for the model is the distance between the company and the customer's location. The customer's location coordinates were obtained from the company and used to calculate this distance using both road (d_j) and Euclidean distances (de_j) on the map. The Euclidean distance was employed for drones, whereas the road distance was utilized for classic and electric motorcycles.

d_j = delivery distance for *order j* for road delivery

de_j = delivery Euclidean distance for *order j*

ii. CO₂ emissions calculation

The values for CO₂ emissions per kilometer for electric motorcycles(e-motorcycles) and classic motorcycles were obtained from the literature [99]. The Honda Super Cub C125 has an internal combustion engine that runs on gasoline. It has a 125-cc fuel-injected engine [134]. In this study, e-motorcycles and drones were proposed as an alternative to the Honda Super Cub C125, which is used for deliveries in the company (Figure 3.1a).

Similar to Park et al.'s study [99], the Lexmoto Valencia 125 is the vehicle model presented as an alternative e-motorcycle (Figure 3.1b). This motorcycle's maximum speed is 66 mph (105 kmh) and it has a 12-voltage battery [135]. The maximum distance it could travel with a fully charged battery is calculated as 40 km.



Figure 3.1. a) Honda Super Cub C125 Motorcycle [134] b) Valencia Motorcycle [135]

This study considered three different kinds of drones, one type of electric motorcycle, and one type of traditional motorcycle. The CO₂ emission value, delivery cost, and maximum speed per hour for the small drone (D1) were obtained from the literature [99]. The drone model that was chosen was the MD4-1000 (Microdrones GmbH: Siegen, Germany). This particular model of microdrone uses a 22.2 V, 13,000 mAh battery that provides an average flight duration of 45 minutes and a maximum speed of 12 m/s [99]. It has a maximum payload capacity of 1.2 kg. The maximum distance that D1 may reach with a fully charged battery was established based on its maximum speed per hour. From the literature, the flying range of D1 is determined to be 1km.

This study considered two additional types of drones (D2 and D3) with different payload and range parameters. The technical characteristics and CO₂ emissions of D2 and D3 were obtained from the website of a drone retail company[136]. These are the Aurelia X4 Standard which stands for D2 and the Aurelia X6 Standard which stands for D3. Aurelia X4 is a quadcopter drone (Figure 3.2a) that carries a maximum of 1.5 kilograms (3.3 lb). It has a total 40-minute travel time and a 2.4 km flying range. A larger drone, Aurelia X8 Standard is a octocopter with 8 rotors (Figure 3.2b) that is capable of carrying up to 8 kilograms (17 lb) and flying for up to 45 minutes. Its flight range is 2.4 km [136].



Figure 3.2. a) Aurelia X4 Standard [136] b) Aurelia X8 Standard [136]

The calculation of CO₂ emissions per kilometer for D2 and D3 during the delivery process involves determining the energy consumption of the drone batteries in kilowatt-hours per kilometer and the CO₂ emission during power production in kilograms per kilowatt hour. The formulas are presented in Equations 3.1 and 3.2.

$$EC_i = \frac{Cp_i}{R_i} \quad (3.1)$$

$$Ed_i = EC_i * E \quad (3.2)$$

In Equations 3.1 and 3.2;

EC_i = energy consumption per km for *drone i*

Cp_i = battery capacity (KWh) for *drone i*

R_i = range (km) for full capacity battery for *drone i*

E = CO₂ emission for electricity production (kg/KWh)

Ed_i = CO₂ emission per kilometer for *drone i*

The value E was taken from the Republic of Turkey Ministry of Energy and Natural Resources 2021 Turkey Electricity Generation and Electricity Consumption Point Emission Factors Information Form [137].

iii. Delivery time calculation

When delivery is done with motorcycles, the time it takes to transport the packages is calculated for each order location based on the map. The probability density functions for motorcycle time were established by Chi-square statistical analysis. The delivery time for the drone was

calculated by multiplying the duration it takes for the drone to go 1 km with the Euclidean distance between the delivery point and the company. The duration of a drone for a distance of 1 km is variable and depends on which type of drone.

iv. Delivery cost calculation

Delivery cost refers to the expense of fuel for the purpose of delivery. The delivery cost per kilometer values for D1 and e-motorcycles were taken from the literature [99].

The delivery cost values of D2 and D3 were derived using the technical specifications of these drones and the cost of producing 1 kilowatt-hour of electricity. The technique of calculating the delivery cost for D2 and D3 involves figuring out the energy consumption of the drone batteries in kilowatt-hours per kilometer and the cost of power production in Turkish lira per kilowatt hour. The provided formulas are stated in Equation 3.3.

$$TC_{ij} = EC_i * C * de_j \quad (3.3)$$

In Equation 3.3;

TC_{ij} = delivery cost for *drone i* each order *j*

C = electricity charge $\frac{\text{TL}}{\text{KWh}}$

Energy cost values were obtained based on the Electricity Invoice Tariff Tables provided by EMRA [138].

The delivery cost per kilometer for a classic motorcycle was calculated by considering the fuel consumption for 100 km and per liter of petrol prices in Turkey. The formula is given in Equation 3.4.

$$TC_{kj} = EC_j * Cg * d_j \quad (3.4)$$

In Equation 3.4;

TC_{kj} = delivery cost for *motorcycle* each order *j*.

EC_j = energy consumption for *motorcycle*

$$C_g = \text{gasoline price} \frac{\text{TL}}{\text{km}}$$

Table 3.1. provides the emission and cost values per kilometer for vehicle types, as derived by these formulas.

Table 3.1. Input values for D2 and D3

Vehicle	CO2 emission value per km (kgCO ₂)	Delivery Cost per km (TL)
D2	0.00032	0.00353
D3	0.01021	0.128603

3.1.2. Software used in the study

The simulation models were established using Arena program version 15.10.00. Arena is a simulation software program that offers an extensive framework for creating models for many different kinds of purposes [139], such as re-engineering, manufacturing, logistics, etc. It enables a modeler to assemble modules, or boxes with various shapes, to represent processes or logic, to create a trial model [140]. From the analysis of input data to the analysis of simulation output data, it covers every stage of a simulation project. Expanding upon the features of Systems Modeling's previous products, SIMAN and Cinema, Arena employs a hierarchical structure to provide the user with the autonomy of a simulator and the power of a simulation language [141]. This program makes flowchart modeling methodology possible, which eliminates the need for bespoke programming by providing an extensive set of pre-defined building fragments to describe the process. It has many benefits, including better visibility into the impact of system or process changes, investigating possibilities for novel techniques or procedures without interfering with the current system, identifying and resolving issues, etc. [142]

3.2. Methods

The method considered in this study consists of 4 steps. In the first step, the simulation model of our study was generated. Subsequently, 7 scenarios that suggest 4 alternative vehicles to the existing classic motorcycles were generated and modeled, then the results were optimized with

OptQuest. The results of the mathematical models were compared by utilizing the TOPSIS method. The methodology of the study is given in Figure 3.3.

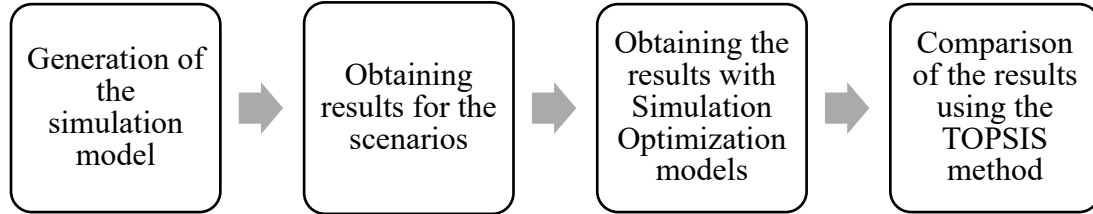


Figure 3.3. Method flow of the study

3.2.1. Simulation modeling

In the first stage of the study, a simulation model was generated and implemented using the Arena program. During the generation of the simulation model, order times, the content of the orders and the location of the orders parameters were also considered in addition to the vehicle used in the company.

By reflecting the cause-and-effect relationships of a theoretical or actual physical system to a computer model, a simulation is a modeling approach that enables the behaviors of the real system to be observed in the computer model under different circumstances. The widespread usage and acceptance of simulation as a tool in operations research and systems analysis can be attributed to advancements in simulation methodology, special-purpose simulation languages, and high computational capabilities for affordable operational costs [143].

In all stages of the acquisition cycle and for all applications—including requirements definition, program management, design and engineering, effective test planning, result prediction, supplementary testing and evaluation, manufacturing, and logistics support—modeling and simulation have grown to be highly significant tools. There are three categories of models and simulations: living, constructive, and virtual. Systems are represented by virtual simulations in both physical and electronic forms. Constructive simulations illustrate a system and how it is employed. Live simulations are computer-generated operations that use actual operators and hardware [144].

3.2.1.1. The fundamental processes of a simulation model

For the simulation model to be successful, certain stages need to be followed in the application process [145]:

1. Definition of the problem: Identifying the problem and outlining the study's objectives are the primary steps in the process. Through impartial observations of the process under study, the problem has been better identified. It is crucial to carefully assess if simulation is the proper tool for the problem being studied.
2. Project organizing: Tasks of the project are divided into work packages, each of which has a responsible party assigned to it.
3. System description: In this step, the components of the system to be modeled and the performance metrics to be examined are identified.
4. Model construction: Creating the appropriate model involves understanding the fundamentals of the system behavior and comprehending how the real system operates.
5. Data collection and analysis for input: The kind of data to be gathered is decided upon once the model has been developed. Either novel information or pre-existing data is obtained. Distributions in theory are adapted to data.
6. Model translation: The language used for programming is translated from the model.
7. Validation and verification: The process of verifying that the model behaves as anticipated frequently involves debugging or animating the model. Validation ensures that the model accurately represents reality and that there are no substantial differences between it and the actual system.
8. Experimentation and analysis: Constructing the alternative model or models, conducting the simulation runs, and statistically comparing the performance of the alternative(s) system with the real system are the steps involved in experimentation.
9. Documentation and implementation: Written reports and/or presentations serve as documentation. The study's conclusions and consequences are examined. The optimal path of action is determined, suggested, and supported.

These steps are basically shown in Figure 3.4.

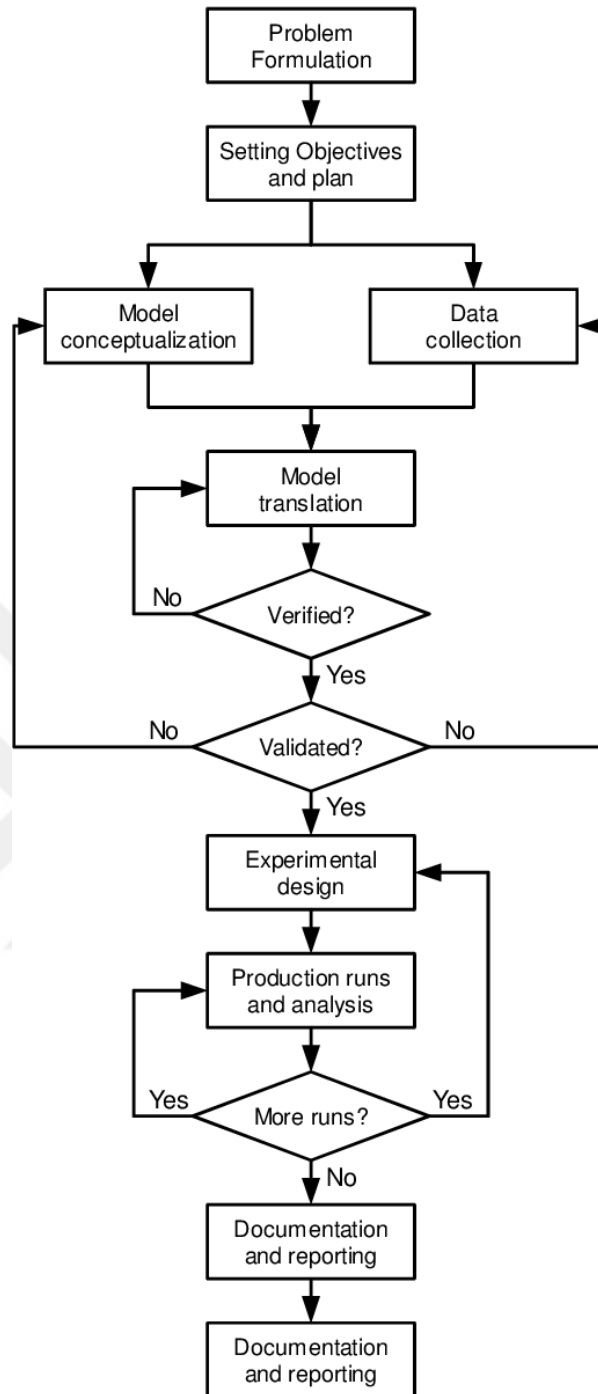


Figure 3.4. Methodology for basic simulation modeling [146]

3.2.1.2. Analysis of model's outputs

Simulation Length: The period that the simulation model runs to determine performance criteria is known as the simulation length [147].

Warm-up Period: The time until the system continues in a constant manner is referred to as the warm-up period. Taking the warm-up period into account ensures that the system results are accurate and therefore can be interpreted correctly [147].

In this study, the simulation model was run for 1 year to determine the replication adequacy in the established model. The warm-up period was calculated with the 'Welch Graph Method'. The flow of calculations in this method is as follows [148]:

- The first step is to run the 'n' number of replications with simulation length 'm'. m has to be big enough and the $n \geq 5$ condition has to be fulfilled.
- For Y_{ji} $j = 1, 2, \dots, n$ and $i = 1, 2, \dots, m$; the averages of the observations in each replication (Y_{ji}) are calculated.
- The replication means (Y_i) are then calculated with Equation 3.5.

$$\bar{Y}_i = \sum_{j=1}^n \frac{Y_{ji}}{n} \quad i = 1, 2, \dots, m \quad (3.5)$$

- Moving averages of replication averages, $Y(w)_i$, is calculated as in Equations 3.6 and 3.7. The symbol 'w' stands for the weight value. In this step, the equations $w \leq [m/4]$ and $w \leq [m/2]$ [148] are taken into account in calculations.

$$Y_i(w) = \frac{\sum_{s=-w}^w \bar{Y}_{i+s}}{2w+1} \quad i = w+1, w+2, \dots, m-w \quad (3.6)$$

$$Y_i(w) = \frac{\sum_{s=1}^{i-1} \bar{Y}_{i+s}}{2i-1} \quad i = 1, 2, \dots, w \quad (3.7)$$

- Then, a graph is created in line with the values obtained from these calculations. By examining the graph, the time when the system goes to a steady state, that is, the warm-up period is determined.

Determination of Replication Number: The number of replications was determined using the 'Fixed Sample Size Method' and the 'Relative Error (g) Formula'.

To calculate the number of replications with relative error, the Equation 3.8 was utilized [148]:

$$n_r^*(\gamma) = \min \left\{ i \geq n: \frac{t_{t-1, 1-\frac{\alpha^*}{2}} \sqrt{S^2(n)/i}}{|\bar{X}(n)|} \leq \gamma' \right\} \quad (3.8)$$

The formula $\gamma' = \frac{\gamma}{1+\gamma}$ indicates the corrected relative error.

In Equation 3.8;

n : Number of replications performed at the beginning,

i : Number of replications required,

$\bar{X}(n)$: The average of n initial replications,

$S(n)$: The standard deviation of the initial n replications,

α : Importance level,

γ : Indicates relative error value.

In order to obtain better results, both the significance level (α) value and the relative error (γ) value should be between 1% and 5%. At least 10 replicates have to be performed initially to determine the number of replications. When substituting the values for $i = n$ in the formula above, if the value found is less than or equal to γ' , the initial number of replications is sufficient. In the opposite cases, new values have to be calculated in the formula by increasing the value of i and finding the required number of replications [149].

Standard Error: It indicates how well the samples selected from a population represent the population. The standard error of the mean is the standard deviation of the sample means. Its calculation is based on the formula $\sigma_{\bar{X}} = \frac{s}{\sqrt{n}}$. In this formula s is the standard deviation of the sample and n is the sample size.

A small standard error indicates that most sample means are the same as the population mean, so the selected sample is an accurate representation of the population [149][150]. The adequacy of the number of replications is tested by calculating the standard error.

3.2.1.3. Assumptions

A total of nine assumptions were considered during the study. These were:

1. One package's demand is represented by each delivery location.
2. Drones have a restricted payload, therefore they are able to carry light items.
3. Only one item could be carried by each drone.
4. Drones have to take off and come back to the depot.
5. The Euclidean distance governs drones' movement.
6. The drones are moving at a constant rate (speed).
7. The effect of weather on travel speed and travel time is not considered.
8. The service time for delivery includes the duration of travel, as well as the time required for the UAV to land and take off.
9. The costs of maintenance are not considered.

3.2.2. Obtaining results for scenarios

In order to integrate e-motorcycles and drones into the system, alternative simulation modeling was developed to the basic simulation model. In this modeling, 7 scenarios which include 5 alternative transportation modes (3 types of drones, motorcycle, and e-motorcycle) were suggested in addition to the existing system. The assumptions in Section 3.1.1.3 were taken into account when generating these scenarios. In this step, scenarios including the combination of motorcycle-drone, drone-e-motorcycle and drone-drone transportation modes were modeled. MD4-1000, Aurelia X4 Standard, and Aurelia X6 Standard models were utilized in drone-drone transportation mode scenarios. All the parameters considered in the initial modeling, such as order times, were also taken into account in this modeling.

3.2.3. Simulation-optimization model

The method of determining the most suitable input variable values among all possible values without directly assessing each one is known as simulation optimization. This method aims to maximize knowledge obtained from a simulation experiment while reducing the consumption of resources [151]. Arena has an OptQuest tool to implement this method. A generic optimizer,

i.e. OptQuest, enables a successful separation of the optimization solution process from the simulation model. It enhances search algorithms, including new tools for solution analysis and more effective algorithms for combining solutions, and enables users to establish bounds on objective functions as well as integer and linear constraints like employee allotments and budget constraints [15]. This tool also enables users to identify the best solutions within the simulation models, which improves Arena's analytical skills [153].

Using the Optquest tool, all scenario model results were obtained and compared using TOPSIS, one of the multi-criteria decision-making methods (MCDM).

3.2.4. TOPSIS method

TOPSIS is a method used for analyzing decisions that involve multiple criteria. It evaluates a group of choices according to predetermined criteria [154]. The underlying principle of it is that the optimal answer is the one that is furthest from the negative ideal and closest to the positive ideal. An overall index that is determined by calculating the distances between the ideal solutions and the alternatives is utilized to rank them [155]. This method allows to provide an optimal solution depending on certain parameters. It can be used in the management of many resources (such as energy), in making the best management depending on environmental or health conditions, in logistics systems, and many other areas.

There are seven stages that compose the entire TOPSIS process. These steps are as follows [156]:

- Constructing an assessment matrix with m alternatives and n criteria, where each alternative's intersection with a criteria is indicated as x_{ij} . This matrix is mathematically shown as $(x_{ij})_{m \times n}$.
- Following that, $(x_{ij})_{m \times n}$ matrix is normalized to create the normalized matrix as in Equation 3.9.

$$R_{ij} = a_{ij} / \sqrt{\sum_{k=1}^m a_{kj}^2} \quad i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \quad (3.9)$$

- The weighted normalized decision matrix V is calculated after the normalized decision matrix has been formed according to Equation 3.10.

$$V_{ij} = w_j \times r_{ij} \quad \forall i, j, w_j \text{ is the weight of criterion } j. \quad (3.10)$$

- Equation 3.11 and Equation 3.12 indicate determining both the positive and negative ideal solutions.

$$A^+ = (\max_i v_{ij} \mid j \in J), (\min_i v_{ij} \mid j \in J) \quad (3.11)$$

$$A^- = (\min_i v_{ij} \mid j \in J), (\max_i v_{ij} \mid j \in J) \quad (3.12)$$

The negative ideal solution is also referred to as the anti-ideal solution and maximizes the cost criteria and minimizes the benefit criteria and attributes. In contrast, the ideal solution maximizes the benefit criteria and attributes and minimizes the cost criteria [157]. The worst performance values constitute the negative ideal solution, whereas the one that is closest to the ideal solution is the best option [158].

- Equation 3.13 and Equation 3.14 indicate determining the difference between each competitive option and the positive and negative ideal solutions:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad i = 1, 2, 3, \dots, m \quad (3.13)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad i = 1, 2, 3, \dots, m \quad (3.14)$$

- The options are ranked by comparing their C^+ values. C^+ values are calculated as equation 3.15.

$$C_i^+ = S_i^- / (S_i^- + S_i^+) \quad i = 1, 2, 3, \dots, m \quad (3.15)$$

where $0 \leq C_i^+ \leq 1$.



4. RESULTS AND DISCUSSION

4.1. Simulation Model

In accordance with the approach developed from this study, a simulation model of the system was established. In the first step of the simulation model, statistical analysis of the data was performed. In the next steps, scenario analysis and simulation optimization models were generated for these scenarios. The TOPSIS method, one of the MCDM methods, was used to prioritize the scenarios and the most suitable scenario for delivery was determined.

4.1.1. Statistical analysis

In the statistical analysis phase, the variables of time between orders (minutes), order weights (kg), distance to the order location (km and Euclidian), and transportation time (minutes) based on distance were statistically examined with the Chi-Square test of goodness of fit in the Statistica program. As a result of this test, the probability distributions that best fit the data were determined. Figure 4.1 shows the Statistica program screen for distance to the order location (km). According to this figure, the analysis was performed for a log-normal distribution. The p-value is a criterion for rejecting a statistical hypothesis test. In Chi-Square tests, if the p-value is greater than 0.05 at the 95% confidence level, the H_0 hypothesis is rejected, indicating that the data fit the distribution being tested. In Figure 4.1, the p-value is 0.07512. This indicates that the distance to the order location fits the tested log-normal distribution.

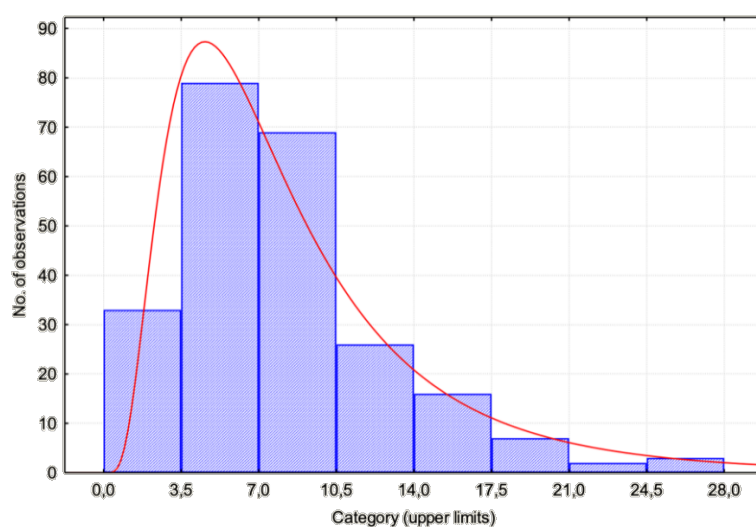
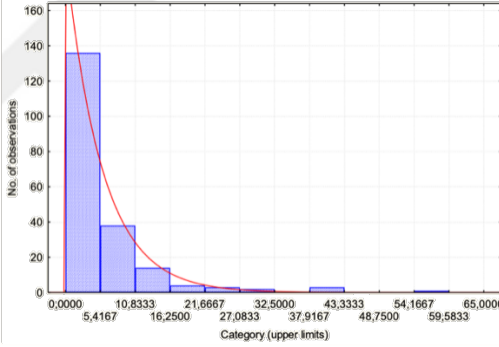
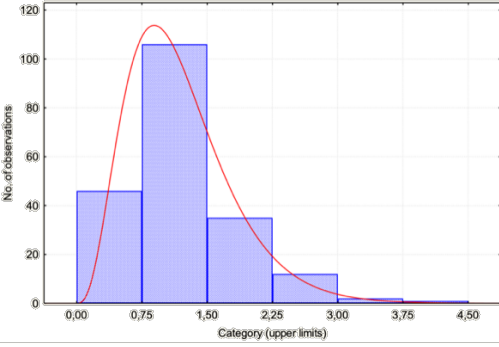


Figure 4.1. Distribution of distance

Chi-Square tests were performed for the time between orders (minutes), weights of orders, distance to the order location (km and Euclidian), and delivery time (minutes) to the order location. Table 4.1 shows the probability distributions and parameters that fit the data for each uncertainty source. When the data analysis results in Table 4.1 are examined, it is seen that the arrival time (minutes) fits the Exponential Distribution, the order weights (kg) fit the Gamma Distribution, the distance to the order location (km) fits the Log-normal Distribution, the value of the distance to the distance to the order location (Euclidian) fits the Log-normal Distribution and the delivery time depending on the distance (minutes) fits the Log-normal Distribution ($p > 0.05$).

Table 4.1. Data analysis results

Data	Distribution	P value	Chi-Square Test
The time between orders (minutes)	Exponential (0,176315)	0,1116 1	
Order weights (kg)	Gamma(0.29967,3.9719 4)	0,1054 4	

The distance to the order location (km)	Log-normal (1,9567, 0.436266)	0,0751 2	
The distance to the order location (Euclidian)	Log-normal (1.30, 0.81297)	0,0561 6	
Transportation time due to distance (minutes)	Log-normal (2.49975, 0.20516)	0,0582 1	

4.1.2. Current system analysis

In its current system, the company delivers all orders to customers with classic motorcycles. The company's vehicle capacity is 4. With the simulation model generated according to the time between orders and order delivery location, the amount of emission and fuel cost in the current system were obtained.

4.1.2.1. Output analysis

For the results of the simulation study to be relevant, output analysis was performed. For determination of the warm-up period, determination of the replication (run) number, and validation with the real system were conducted for this purpose.

Warm-up Period: The warm-up period of the simulation model was calculated with the formulas in Equations 3.5-3.7. As a result of this calculation, the warm-up period graph in Figure 4.2 was obtained. Since this graph becomes stationary after the 35th day, the warm-up period was taken as 35 days.

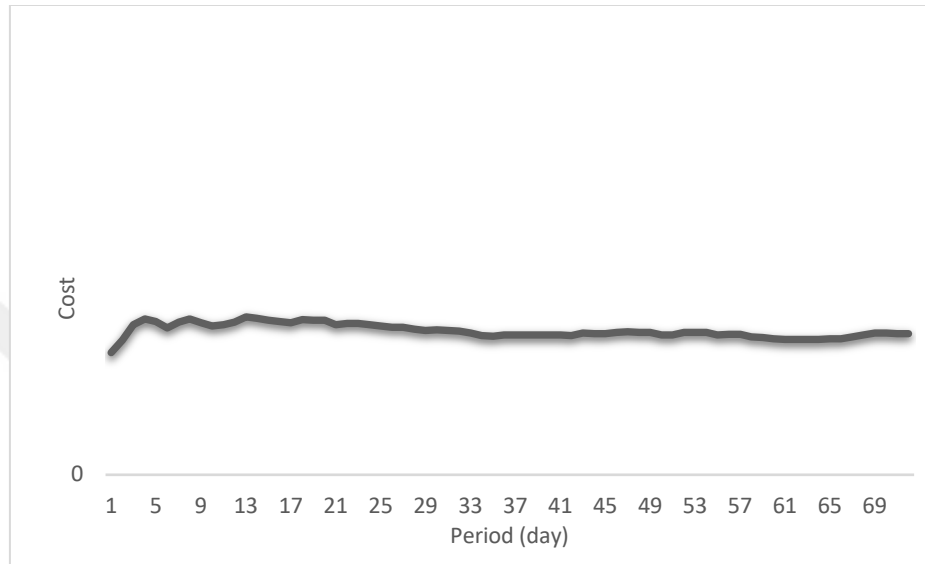


Figure 4.2 Warm-up period

Calculation of Number of Replications and Relative Error: 10 replications were performed and the mean of 10 replications was calculated as 54583,7. The number of replications was calculated according to Equation 3.8 and in the case of 10 replications, the value in Equation 3.4 (0.01) was smaller than the relative error (0.09). This shows that 10 replications with a 10% relative error is sufficient.

Simulation Length: The length of the simulation is 365 days.

Verification and Validation: Verification refers to the process of ensuring that a model is appropriate in terms of its computer or logical structure and that it accurately reflects the intended structure. System verification was accomplished by the carrying out of checks.

Validation was performed to measure whether the simulation results reflect the real system. For this purpose, the simulation results were compared with the observations taken from the real system by independent t-test. The Hypothesis of the Independent t-test is determined as follows:

H_0 : There is no meaningful difference between delivery cost in system data of simulation and real system observations.

H_1 : There is a meaningful difference between delivery cost in system data of simulation and real system observations.

The significance thresholds for the independent samples test in the cases of equal variances assumed and not assumed were 0.792 and 0.792, respectively. Both instances had p-values greater than 0.05. This finding suggests that the amount of time spent using simulation system data and actual system observations does not significantly differ, and the model accurately depicts the real system. In other words, model validation is provided.

In the scope of the study, it is aimed to determine the vehicle fleet in case the companies switch to e-vehicle use to minimize greenhouse gas emission values and delivery costs. For this reason, different scenarios were generated for the vehicle fleet.

4.2. Scenario Analysis and Results

Scenario 1 – Combination of D1 and Classic Motorcycle

In Scenario 1, the D1 is the only new addition to the existing system, alongside the motor already utilized by the corporation. The flow chart for this scenario is provided in Figure 4.3. The D1 has a range of 1 kilometer and a payload capacity of 1.2 kilograms. Therefore, if the Euclidian distance of the order location is more than 1 km and/or the weight of the order is more than 1.2 kg, the delivery is made only with the motorcycle. If the delivery of the order by drone is appropriate, a simulation model is generated according to the delivery with the vehicle with the minimum average number of waiting orders.

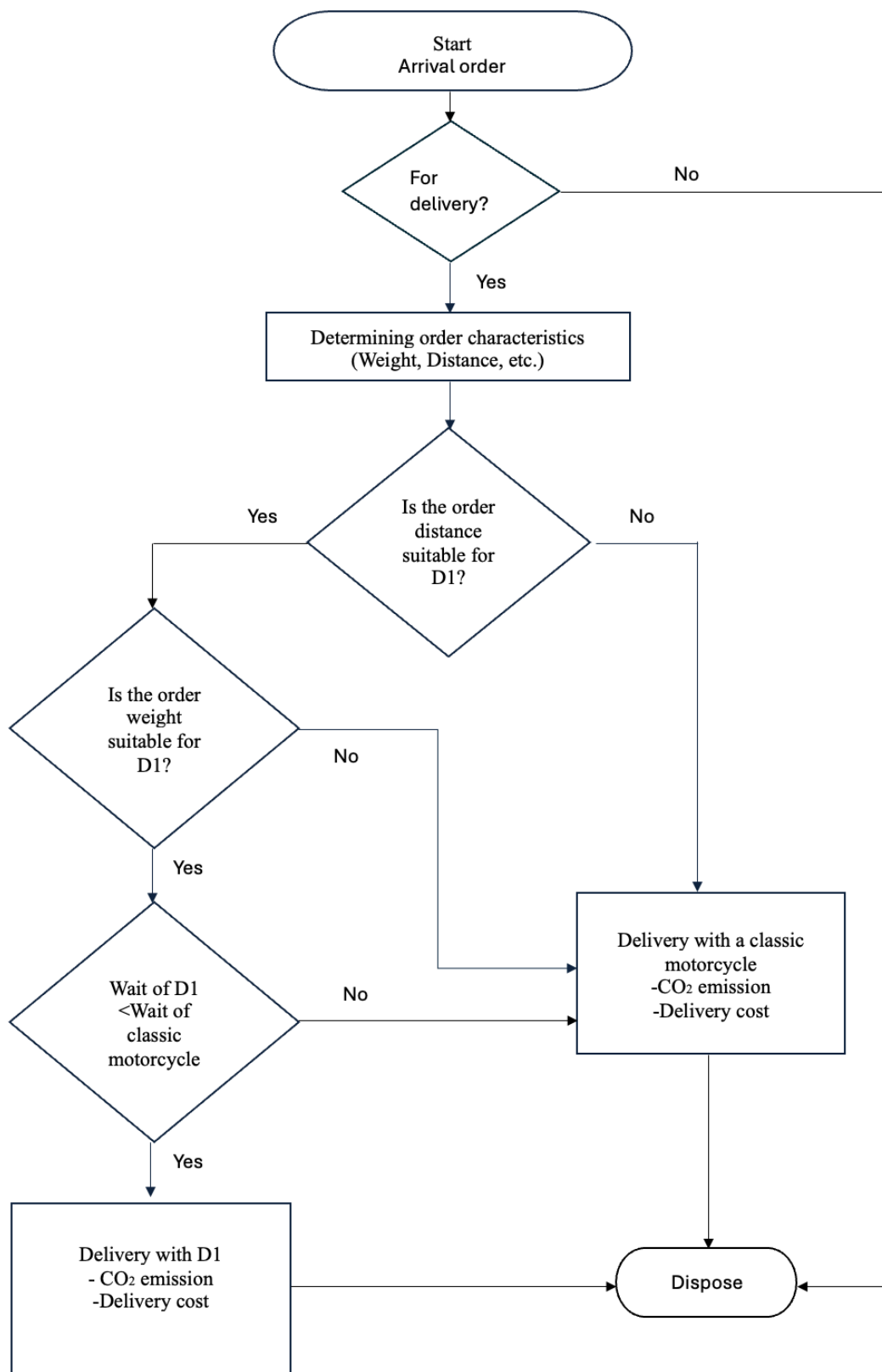
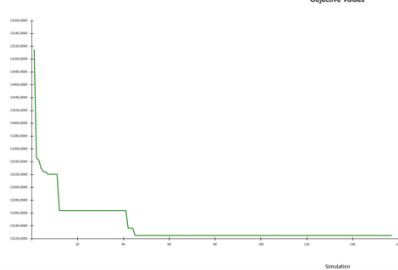
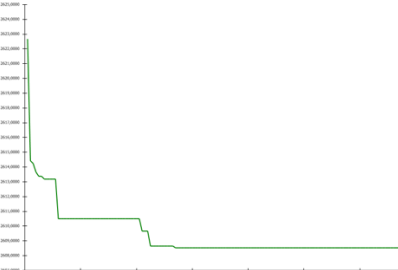


Figure 4.3. Flowchart of D1 and classic motorcycle combination

The simulation model was run with a warm-up period of 35 days, a replication length of 365 days, and 10 replications. Considering the flow in Figure 4.3, the simulation model was run with 1 drone and 1 classic motorcycle. Drone utilization rate, engine utilization rate, CO₂ emissions, and delivery cost values were calculated. The simulation-optimization model of this model was modeled in the Arena OptQuest tool. In the OptQuest model, the minimum value for engine and drone resources was set as 1 and the maximum value was set as 15. Considering CO₂ emission and cost minimization objectives separately, the ideal number of vehicles for each objective function was determined. In Scenario 1, where CO₂ emission is used as the objective function in OptQuest, there are 3 D1 vehicles and 6 classic motorcycles.. If the delivery cost of the objective function is minimized, the number of vehicles is determined as 3 drones and 6 classic motorcycles. According to the obtained vehicle values, the delivery cost and CO₂ emission value were determined as 53225.089115 kg-CO₂/year, and 2608.533695 TL/year respectively. In the models, the same solutions were obtained when the objective function was CO₂ emission and delivery cost. The graph of the OptQuest model and the results obtained are given in Table 4.2.

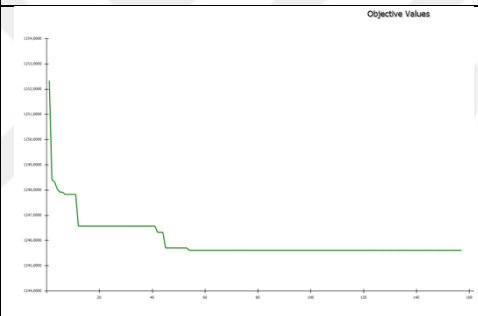
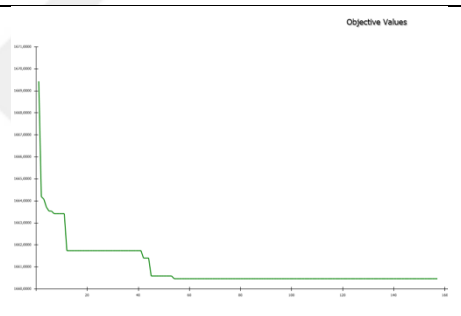
Table 4.2. Combination of D1 and classic motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
		
# of D1	3	
# of Classic Motorcycle	6	
Delivery cost (TL/year)	53225,089115	
CO ₂ emission (kg-CO ₂ /year)	2608,533695	

Scenario 2 – Combination of D1 and E-Motorcycle

In contrast to Scenario 1, Scenario 2 considers the motorcycle as an electric motorcycle. Section 3.1 provides the e-motorcycle's technical specifications. With the Arena simulation model OptQuest tool, the ideal number of vehicles for each objective function was determined by considering CO₂ emission and cost minimization objectives separately. In Scenario 2, the objective in OptQuest was to minimize both cost and CO₂ emissions. As a result, the optimal number of D1 was determined to be 3, while the optimal number of e-motorcycles was determined to be 6. The OptQuest model's graph and its associated results are presented in Table 4.3.

Table 4.3. Combination of D1 and E-Motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
		
# of D1	3	
# of E-motorcycle	6	
Delivery cost (TL/year)	1245,614011	
CO ₂ emission (kg-CO ₂ /year)	1660,467209	

Scenario 3 –Combination of D2 and Classic Motorcycle

In Scenario 3, the case of using a medium drone (D2) instead of a small drone (D1), which is different from Scenario 1, is analyzed. The D2 technical requirements are provided in Section 3.1. Based on these characteristics, the simulation-optimization model determined that the ideal quantity of D2 is 8, whereas the ideal quantity of classic motorcycles is 1. Table 4.4 shows the results obtained for Scenario 3.

Table 4.4. Combination of D2 and classic motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
# of D2	8	
# of Classic Motorcycle	1	
Delivery cost (TL/year)	21462,045401	
CO ₂ emission (kg-CO ₂ /year)	1027,379149	

Scenario 4 – Combination of D2 and E-Motorcycle

The motorcycle in Scenario 4 is considered an electric motorcycle, in contrast to Scenario 3. The D2 technical requirements are provided in Section 3.1. Considering these parameters, the ideal number of medium drones was determined as 8 and e-motorcycles as 1 with the simulation-optimization model. Table 4.5 shows the results obtained for Scenario 4.

Table 4.5. Combination of D2 and E-Motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
# D2	8	
# E-Motorcycle	1	
Delivery cost (TL/year)	657,044852	
CO ₂ emission (kg-CO ₂ /year)	647,91741	

Scenario 5: Combination of D3 and Motorcycle

In order to account for the varying weights of orders, a drone with a larger payload capacity has been integrated into the system, in addition to the drone type that was evaluated in Scenarios 1 and 2. For this reason, a drone with a payload capacity of 8 kg was also included in the system. The utilization of a classic motorcycle and a D3 with a large payload capacity was assessed in Scenario 5. The payload of D3 is significantly greater than the order weights provided by the company, which enables it to be utilized for deliveries of all weights, similar to motorcycles. As a result, the simulation model shown in Figure 4.4 for Scenario 5 does not include a decision node based on the weight of the product.

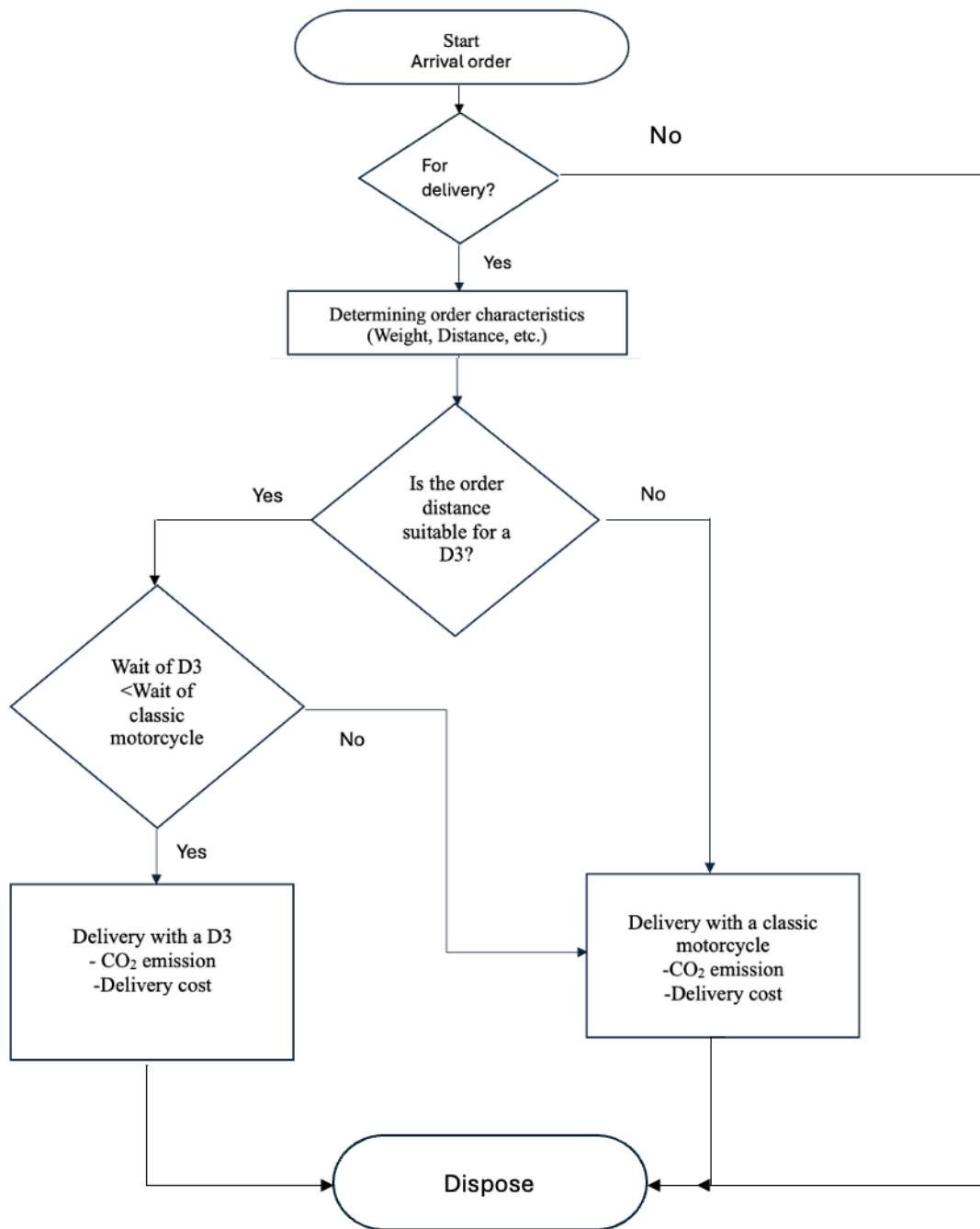
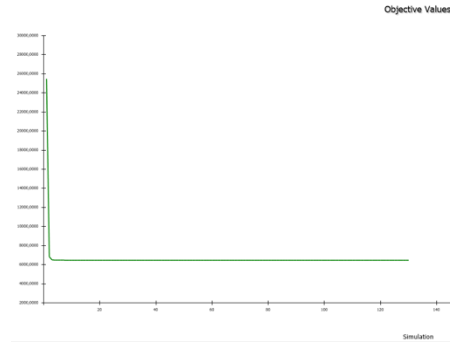
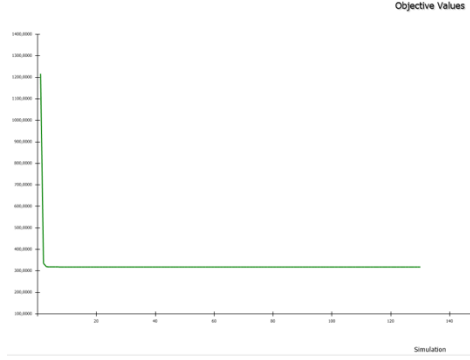


Figure 4.4. Flowchart of D3 and classic motorcycle combination

The simulation-optimization model determined that the ideal quantity of D3 is 13, while the ideal number of motorcycles is 1, taking into account both of their characteristics. The results obtained for Scenario 5 are displayed in Table 4.6.

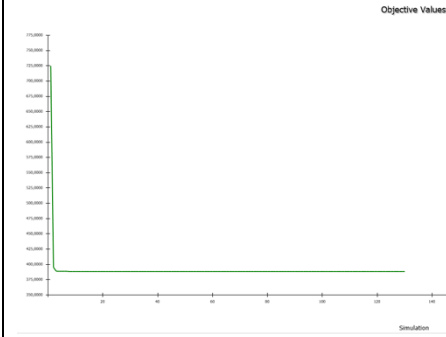
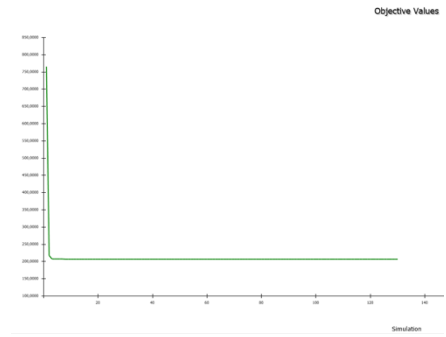
Table 4.6. Combination of D3 and classic motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
		
# D3	13	
# of Classic Motorcycle	1	
Delivery cost (TL/year)	6465,531932	
CO ₂ emission (kg-CO ₂ /year)	317,904286	

Scenario 6: Combination of D3 and E-Motorcycle

Scenario 6 investigated the motorcycle's classification as an e-motorcycle, in contrast to Scenario 5. The simulation model adopted the characteristics of the D3 and E-motorcycles. According to the simulation-optimization model, the ideal quantity of e-motorcycles is 1, while the ideal quantity of D3 is 13. Table 4.7 displays the model's results.

Table 4.7. Combination of D3 and E-Motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
		
# of D3	13	
# of E-Motorcycle	1	
Delivery cost (TL/year)	388,31568	
CO ₂ emission (kg-CO ₂ /year)	207,062134	

Scenario 7 - Combination of Drones and E-Motorcycle

Scenario 7 only considers the use of electric vehicles for deliveries. In Scenario 7, the D2 and D3 drones were selected due to their identical range values. The scenario excluded the D1 due to the insignificant difference in payload capacity between the D1 and D2. Figure 4.5 illustrates the flow diagram for the delivery process utilizing drones and electric motorcycles. If the weight and range of the orders are suitable for delivery using D2, the delivery is carried out using the transportation vehicle with the minimum waiting time among the three transportation modes. Otherwise, the delivery was carried out utilizing the transportation vehicle with the least amount of time spent waiting between D3 and the e-motorcycle.

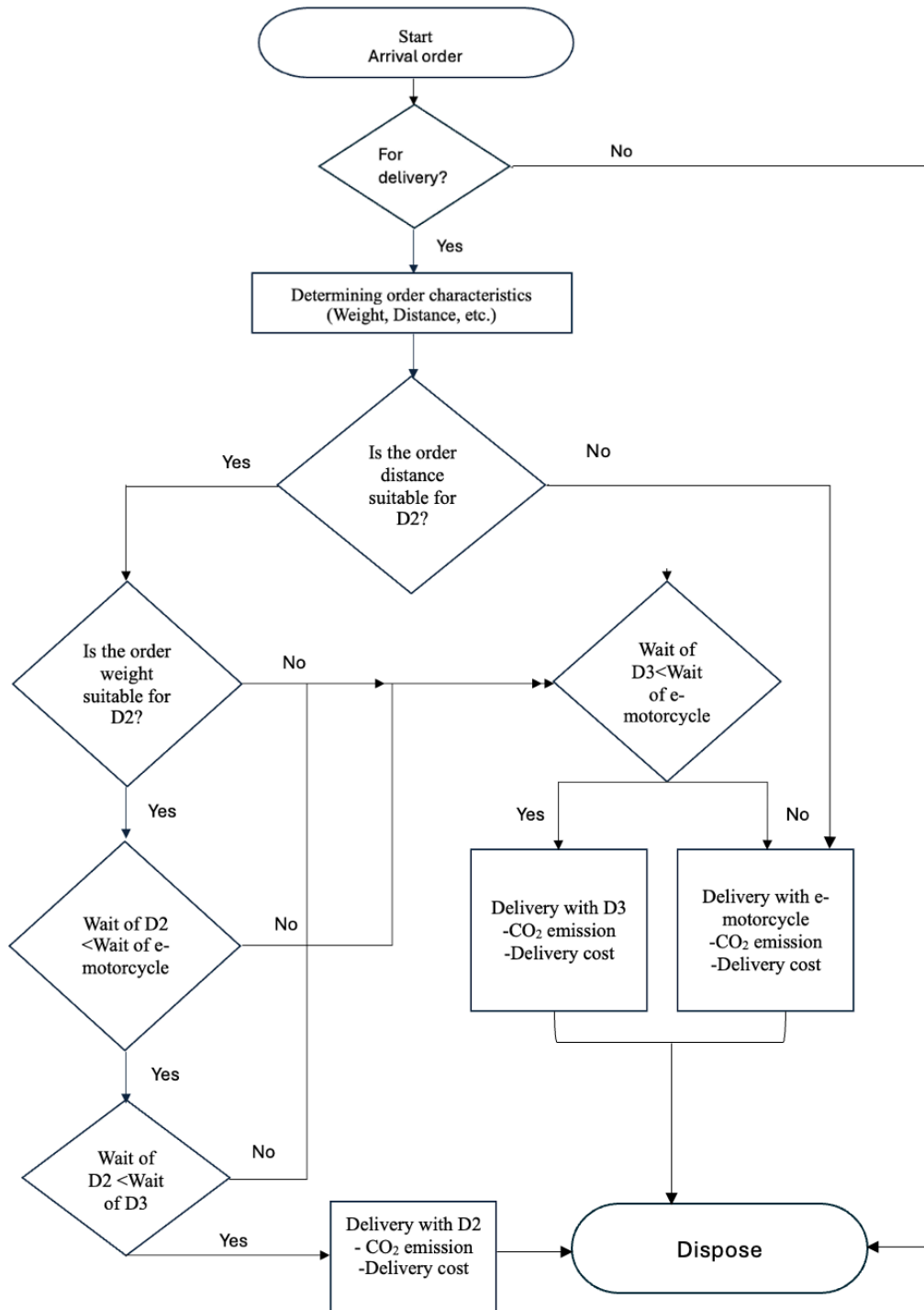
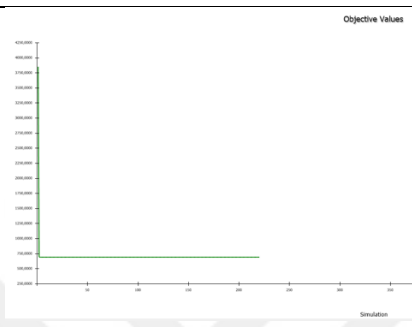
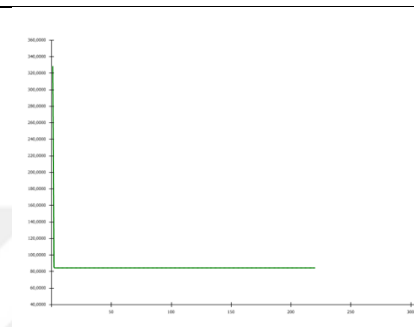


Figure 4.5. Flowchart of E-motorcycle and D2-D3 combination

The ideal amount of vehicles for each objective function was determined by examining the CO₂ emission and cost minimization objectives separately using the Arena simulation model

OptQuest tool. The numbers of D2, D3, and e-motorcycles were determined to be 10, 2, and 13, respectively, when the cost and CO₂ emission were considered the objective functions in OptQuest. Table 4.8 contains the OptQuest model graph and the results that were obtained.

Table 4.8. Combination of D2-D3 and E-Motorcycle

Simulation-Optimization model	Cost minimization	CO ₂ emission minimization
		
# of D2	10	
# of D3	2	
# of E-Motorcycle	13	
Delivery cost (TL/year)	692,88613	
CO ₂ emission (kg-CO ₂ /year)	84,571121	

In scenarios 5 and 6, considering D3 and a motorcycle, the ideal option is to have one motorcycle, while in scenario 7, where D2, D3, and the motorcycle are all considered simultaneously, the value of the motorcycle is determined to be 13. The reason for this is that when transporting with a payload value greater than 1.5 kg and/or when the waiting time for D2 is long, delivery is made with the minimum waiting time between D3 and the e-motorcycle. Based on the technical specifications of D3 and the motorcycle, the e-motorcycle has lower CO₂ emission and delivery cost values compared to D3. By considering the objective functions of minimizing cost and CO₂ emissions, the optimization model increases the capacity of the e-motorcycle, reduces waiting times, and enables delivery with the motorcycle.

Considering different types of vehicles in the scenarios will result in different investment costs for each scenario. The impact of the investment cost per use, depreciation cost, and the degree to which speed affects the system could not be reflected in the simulation model since no data could be obtained from the literature or practice. For this reason, for these criteria, scenario prioritization was made with TOPSIS, one of the MCDM methods, integrated into the system with expert opinion evaluation.

4.3. Scenario Prioritization using MCDM

The TOPSIS approach has been utilized to evaluate the solutions obtained for 7 different scenarios. Table 4.9 shows the CO₂ emission, delivery cost and normalized investment cost values for each scenario. CO₂ emission and delivery cost values were obtained from the simulation optimization model. If the solution includes a classic motorcycle and requires more than the company's existing four engines, the cost will increase by the amount needed to purchase more motorcycles. The cost of the vehicles varies depending on the dealer and the discount. Consequently, the investment cost for each scenario was calculated using the purchase prices received from an online dealer's website. The purchase price of each scenario was normalized by allocating it proportionally to the overall purchase cost of seven scenarios. The values of CO₂, delivery cost, and normalized investment cost for each scenario are presented in Table 4.9.

Table 4.9. Comparison of the scenarios

Scenario	Delivery cost (TL/year)	CO₂ emission value (kg- CO₂/year)	Investment Cost
S1	53225,08912	2608,533695	0,06816707
S2	1245,614011	1660,467209	0,06544039
S3	21462,0454	1027,379149	0,07850665
S4	657,044852	647,91741	0,0866867
S5	6465,531932	317,904286	0,22682456
S6	388,31568	207,062134	0,23500461
S7	692,88613	84,571121	0,23937003

Considering the data in Table 4.9, the importance level of each scenario is determined by applying Equations (3.9)-(3.15) and given in Table 4.10.

Table 4.10. Priority of the scenarios

Scenario	S_i^*	S_i^-	Total	C_i
S1	1,185662095	0,39634814	1,58201023	0,2505345
S2	0,471375217	1,025628511	1,49700373	0,68512088
S3	0,461964919	0,815105714	1,27707063	0,63826205
S4	0,175519278	1,138596379	1,31411566	0,86643544
S5	0,394360692	1,060592837	1,45495353	0,72895307
S6	0,39425879	1,162725722	1,55698451	0,74678053
S7	0,40269513	1,181583843	1,58427897	0,74581804

As seen in Table 4.10 and Figure 4.6, Scenario 4 has the highest priority number. Considering the minimization of delivery cost, CO₂ emission value, and investment costs at the same time, the realization of deliveries according to Scenario 4 will be the most appropriate solution for the company.

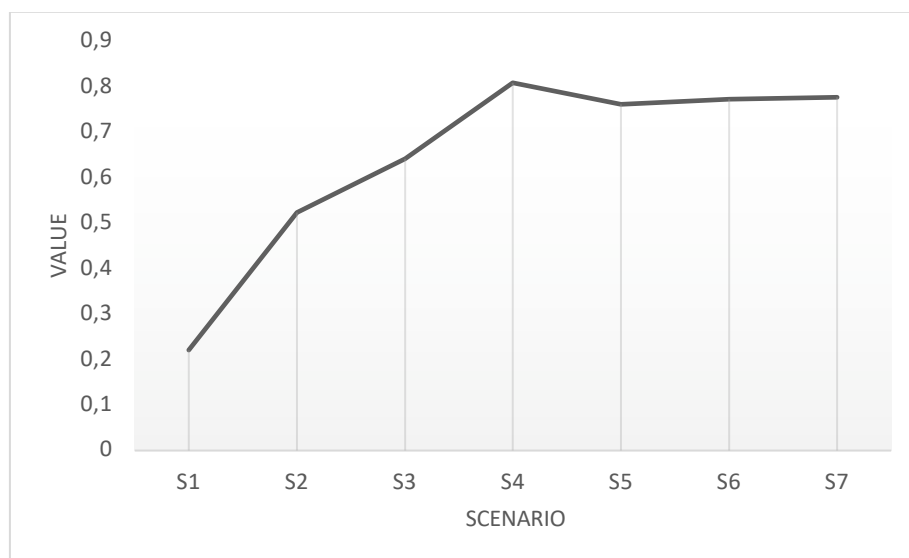


Figure 4.6. Priority of the scenarios

5. CONCLUSION

The rapid development of technology in recent years has resulted in numerous advancements that have significantly enhanced the quality of life. E-commerce, the integration of technology into trade, offers customers numerous benefits when making purchases. As a result, shoppers have altered their buying patterns and currently choose internet shopping over traditional physical establishments. The frequency of deliveries has increased in recent years due to a rise in online shopping. Therefore, companies have had to adapt to this trend in order to remain competitive and ensure timely delivery of orders with this increased demand. Due to the situation, companies have been forced to concentrate on distribution techniques as a means to enhance their revenues. The transportation costs per unit of distance vary based on the quantity and kind of fuel utilized by the delivery vehicles. Nevertheless, the growing quantity of vehicles in operation, along with an increasing number of orders, results in a rise in the consumption of fossil fuels during the operation of internal combustion engine vehicles. Simultaneously, the vehicles utilized release greenhouse gases into the environment at different rates, depending upon the fuel type. The objective is to shift the company's vehicle fleet from fossil fuel-powered vehicles to electric vehicles with the goals of enhancing profitability, establishing an environmentally friendly brand image in the market, and ensuring compliance with legal regulations.

This study developed a simulation optimization model to determine the vehicle fleets that will achieve the companies' goals of minimizing CO₂ emissions and delivery costs during the switch to electric vehicle adoption. In the context of the study, the three different capacities of drones (small, medium, and large) and e-motorcycles were evaluated. In the current system, the company's engine for transportation, which performs on fossil fuels, was also included in the process, and 7 scenarios that include five different transportation vehicles were generated with solutions obtained using the simulation optimization model for each scenario. Different vehicle types and numbers were suggested as optimal solutions for each scenario, resulting in different CO₂ emissions and delivery costs.

Choosing the most suitable scenario for the company among the solutions generated by simulation optimization models can be difficult to decide. The smallest CO₂ emission value was found in Scenario 7, whereas the minimum delivery cost value was acquired in Scenario 6. The number of vehicles to be purchased and the investment expenses change in each scenario.

The simulation-optimization model's ideal solution consists of six motorcycles and three D1s for Scenario 1, six e-motorcycles and three D1s for Scenario 2, eight D2s and one motor for Scenario 3, eight D2s and one e-motor for Scenario 4, thirteen D3s and one engine for Scenario 5, thirteen D3s and one e-motor for Scenario 6, and ten D2, two D3, and thirteen e-motors for Scenario 7. Drones can operate independently owing to remote control software on a computer and complex dynamic automation systems or pre-programmed flight plans [64]. They generally have no need to deal with congestion or intermediate routes when traveling from one place to another. This leads to reduced energy use since it makes the transportation process more efficient. Prioritizing amongst scenarios requires taking into account not only CO₂ emissions and delivery costs, but also their investment cost values. TOPSIS, one of the MCDM approaches, was used to analyze the five scenarios addressed in this study, taking into account three criteria (CO₂ emissions, delivery costs, and investment costs). According to the TOPSIS evaluation, the scenarios are prioritized as follows: Scenario 4, Scenario 6, Scenario 7, Scenario 5, Scenario 2, Scenario 3, and Scenario 1. Although the investment cost is only evaluated for drones since the classic motorcycle in the firm is utilized in Scenarios 1 and 3, the low priority order demonstrates that the usage of electric vehicles is advantageous to companies, even if the investment is significant.

6. RECOMMENDATIONS

The continuous advancement of technology will lead to the increasing use of online shopping in various industries, including grocery stores, pharmacies, pet shops, herbalists, and more. Ignoring these developments and selling with traditional methods will cause companies to fall behind in the market. A digital presence to keep up with competition will pose new challenges that firms will need to manage in order to make profits. While technology makes our daily lives easier, it also has its disadvantages. Access to all kinds of products that can be sold online will reduce the number of people going to physical stores, but the increase in orders placed through applications will lead to an increase in transportation to deliver the order to the customer. Companies may purchase more vehicles in order to increase customer satisfaction and make faster deliveries. This intensity in transportation could increase the combustion of fossil fuels used by internal combustion engines, causing serious damage to the environment. This intensity in transportation increases the combustion of fossil fuels used by internal combustion engines, threatening the environment and, consequently the lives of all living beings. Numerous studies demonstrate that it is possible to integrate electric vehicles, supported by technology, into transportation systems. The fact that these vehicles do not have internal combustion engines could help minimize the harmful effects. Yet these environmentally friendly vehicles are not completely harmless. In addition to their energy consumption, the type of batteries used to run them, and the environmental impact of batteries' recycling, the most important thing is the source of electricity, that is, how the electricity to be used is generated. Carbon dioxide emissions from coal-fired power plants are typically the highest globally, both in terms of overall emissions and particular output. In other words, the negative impact on the environment that EVs generate is related to the source of the electricity that runs them. Between 1973 and 2014, the amount of electrical energy produced by fossil fuels increased by more than four times, from 2348 TWh to 9791 TWh [159], and this indicates the increasing use of fossil fuels as a source of electricity through the years. The power generation operations have been slowly but steadily altering as a result of the realization of the risks posed by global warming. The main development has been the advancement of new renewable energy technologies, especially solar and wind power, which add to the atmosphere's carbon dioxide content without increasing it [159].

In the Turkey Electricity Generation and Electricity Consumption Point Emission Factors Fact Sheet published in 2021, "Electricity Generation Emission Factors by Fuel for Power Plants" were calculated based on the methodology in the "Database Documentation" of the International Energy Agency's "Emission Factors 2021" study (Table 6.1). 36.3% of Turkey's electricity was generated by coal in 2023, followed by natural gas (21.4%), hydraulic energy (19.6%), wind (10.4%), solar energy (5.7%), geothermal energy (3.4%), and other sources (3.2%) [137].

Table 6.1. According to fuel type for power plants electricity generation emission factors by fuel for power plants [137]

Fuel Type	Value (TCO₂M/Wh)	Value (TCO₂eM/Wh)
Lignite	1,152	1,165
Stone Coal	0,994	0,998
Asphaltite	0,953	0,958
Imported Coal	0,806	0,810
Natural Gas	0,374	0,380
Fuel Oil	0,785	0,786
Diesel Oil	0,581	0,582

In order to minimize the damage to the environment, while increasing the use of electric vehicles, the use of renewable energies as the source of electricity should be increased. If the electricity is generated from renewable energy sources, EVs could be significantly environmentally friendly. Increasing the number of plants producing renewable energy is among the measures that should be taken. Therefore, the model may incorporate the use of renewable energies and alternative sources as an electricity generation source for electric vehicle battery charging. The study may also consider the environmental impact in the event that the battery expires. This study enhanced the model by incorporating both a drone and an e-motorcycle. Additionally, the model can include various electric vehicles, such as robots and

e-bikes, expanding the scenarios to identify ideal solutions. Future studies can obtain new solutions based on the energy source and vehicle type, and compare the scenarios using different MCDM techniques, such as weighted MCDM and fuzzy logic methods. Furthermore, the system can incorporate operator costs, depreciation values, and maintenance costs, as well as areas that are inaccessible to the drone and weather conditions within the model.



REFERENCES

- [1] <https://www.walkme.com/glossary/digitalization/#:~:text=Digitization%20is%20simply%20the%20converting,This%20is%20digitization.>
- [2] <https://www.eticaret.gov.tr/cevrimiciegitim/sayilarla-dunyada-e-ticaret-21>
- [3] Paraschiv, D. M., Țițan, E., Manea, D. I., Ionescu, C. D., Mihai, M., & Șerban, O. (2022). The change in e-commerce in the context of the Coronavirus pandemic. *Management & Marketing*, 17(2), 220-233.
- [4] <https://www.simon-kucher.com/en/insights/covid-19-changed-shopping-behaviors-how-consumer-goods-manufacturers-can-capitalize-it>
- [5] <https://www.credencys.com/blog/online-food-ordering-system/>
- [6] <https://www.statista.com/forecasts/891088/online-food-delivery-users-by-segment-worldwide>
- [7] Cho, M., Bonn, M. A., & Li, J. J. (2019). Differences in perceptions about food delivery apps between single-person and multi-person households. *International Journal of Hospitality Management*, 77, 108-116.
- [8] <https://dictionary.cambridge.org/dictionary/english/transportation>
- [9] <https://blog.mihlfeld.com/the-6-modes-of-transportation>
- [10] Gevaers, R., Van de Voorde, E., & Vanelander, T. (2011). Characteristics and typology of last-mile logistics from an innovation perspective in an urban context. In *City distribution and urban freight transport*. Edward Elgar Publishing.
- [11] Poon, W. C., & Tung, S. E. H. (2024). The rise of online food delivery culture during the COVID-19 pandemic: an analysis of intention and its associated risk. *European Journal of Management and Business Economics*, 33(1), 54-73.
- [12] <https://digitalsupplychaintoday.com/f/first-middle-last-mile-logistics>
- [13] https://www.theseus.fi/bitstream/handle/10024/149875/Maksimkin_Igor.pdf?sequence=1
- [14] <https://understand-energy.stanford.edu/energy-services/energy-transportation>
- [15] <https://havakalitesi.ibb.gov.tr/Icerik/bilgi/havakirleticileri#:~:text=SO2%20ve%20ince%20partik%C3%BCllere,veya%20kalp%20hastal%C4%B1%C4%9F%C4%B1%20olan%20ki%C5%9Filerdir>
- [16] <https://auditel.co.uk/are-carbon-emissions-the-same-as-greenhouse-gases/>
- [17] <https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions>
- [18] <https://meersens.com/carbon-dioxide-co2-sources-and-health-impacts/?lang=en#BLOC1>

[19]

https://sustainablemobility.iclei.org/ecologistics/handbook/?gad_source=1&gclid=Cj0KCQjw0_WyBhDMARIsAL1Vz8s93Rh1-9rItcMCuI2XPzOtwx1YMkE0JQVG3jDtzUU-6FuqOJYZnOIaArHREALw_wcB

[20] <https://www.epa.gov/ghgemissions/overview-greenhouse-gases>

[21] <https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions>

[22] KANTAR Worldpanel THE FUTURE OF E-COMMERCE IN FMCG; KANTAR Worldpanel: November 2017.

[23] <https://www.unicef.org/press-releases/air-pollution-accounted-81-million-deaths-globally-2021-becoming-second-leading-risk>

[24] Tollefson, J. (2022). Scientists raise alarm over ‘dangerously fast’ growth in atmospheric methane.

[25] <https://www.pca.state.mn.us/pollutants-and-contaminants/sulfur-dioxide#:~:text=These%20gases%2C%20especially%20SO2%2C%20are,existing%20heart%20and%20lung%20conditions>

[26] <https://www.setteknik.com.tr/azot-dioksit-gazinin-ozellikleri-nelerdir-ve-nasil-tespit-edilir#:~:text=Azot%20dioksit%20kuvvetli%20bir%20oksidasyona,neden%20olan%2C%20a sit%20ya%C4%9Fmurlar%C4%B1n%C4%B1%20olu%C5%9Fturmakta%C4%B1r>

[27] <https://www.unicef.org/press-releases/air-pollution-accounted-81-million-deaths-globally-2021-becoming-second-leading-risk>

[28] Ghajargar, M., Zenezini, G., & Montanaro, T. (2016). Home delivery services: innovations and emerging needs. IFAC-PapersOnLine, 49(12), 1371-1376.

[29] Srinivas, S., Ramachandiran, S., & Rajendran, S. (2022). Autonomous robot-driven deliveries: A review of recent developments and future directions. Transportation research part E: logistics and transportation review, 165, 102834.

[30] Kostrzewski, M., Abdelatty, Y., Eliwa, A., & Nader, M. (2022). Analysis of modern vs. conventional development technologies in transportation—The case study of a last-mile delivery process. Sensors, 22(24), 9858.

[31] Bjorklund, M., 2011. Influence from the business environment on environmental purchasing - drivers and hinders of purchasing green transportation services. J. Purch. Supply Manag. 17, 11–22. <https://doi.org/10.1016/j.pursup.2010.04.002>.

- [32] Lee, C.T., Hashim, H., Ho, C.S., Fan, Y.V., Klemeš, J.J., 2017. Sustaining the low-carbon emission development in Asia and beyond: sustainable energy, water, transportation and low-carbon emission technology. *J. Clean. Prod.* 146, 1–13.
- [33] Ehrler, V. C., Schöder, D., & Seidel, S. 2021. Challenges and perspectives for the use of electric vehicles for last mile logistics of grocery e-commerce—Findings from case studies in Germany. *Research in Transportation Economics*, 87, 100757.
- [34] Machedon-Pisu, M., & Borza, P. N. (2019). Are personal electric vehicles sustainable? A hybrid E-bike case study. *Sustainability*, 12(1), 32.
- [35] <https://ev.hedeffilo.com/ev-gundem/blog/elektrikli-motosiklet-nedir-nasil-calisir-ve-nasil-kullanilir>
- [36] Khandekar, S. S., Kelkar, R., & Poojary, A. E-Motorcycle: A solution to reduction in cost of transportation.
- [37] Figliozzi, M. A. (2020). Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles. *Transportation Research Part D: Transport and Environment*, 85, 102443.
- [38] <https://techcrunch.com/2022/10/07/amazon-scales-back-scout-delivery-robot-program/>
- [39] <https://www.smh.com.au/business/companies/dominos-serves-up-pizza-delivery-robot-20160318-gnlqjc.html>
- [40] Mohsan, S. A. H., Zahra, Q. U. A., Khan, M. A., Alsharif, M. H., Elhaty, I. A., & Jahid, A. (2022). Role of drone technology helping in alleviating the COVID-19 pandemic. *Micromachines*, 13(10), 1593.
- [41] Javaid, M., Haleem, A., Khan, I. H., Singh, R. P., Suman, R., & Mohan, S. (2022). Significant features and applications of Drones for Healthcare: An overview. *Journal of Industrial Integration and Management*, 2250024.
- [42] Mohsan, S. A. H., Zahra, Q. U. A., Khan, M. A., Alsharif, M. H., Elhaty, I. A., & Jahid, A. (2022). Role of drone technology helping in alleviating the COVID-19 pandemic. *Micromachines*, 13(10), 1593.
- [43] Mahajan, G. (2021). Applications of drone Technology in Construction Industry: A study 2012-2021. *International Journal of Engineering and Advanced Technology*, 11(1), 224-239.
- [44] PETROȘANU, D. M., & Pirjan, A. (2022). ADVANTAGES AND CHALLENGES REGARDING THE USAGE OF DRONES IN E-COMMERCE. *Journal of Information Systems & Operations Management*, 16(2).

- [45] Murphy, M. (2016). The future is here: Drones are delivering Domino's pizzas to customers. <https://qz.com/838254/dominos-is-delivering-pizza-with-autonomous-drones-to-customers-in-new-zealand/> <https://techcrunch.com/2016/08/26/flirteyflies-pies-for-dominos-in-new-zealand/>.
- [46] <https://kurumsal.yemeksepeti.com/en/newsroom/yemeksepeti-successfully-delivered-first-meal-with-drone/>
- [47] Nelson, D. (2014). Indian restaurant uses aerial drone to deliver pizza to skyscraper. <http://www.telegraph.co.uk/news/worldnews/asia/india/10848680/Indianrestaurant-uses-aerial-drone-to-deliver-pizza-to-skyscraper.html>.
- [48] https://www.huffpost.com/entry/tacocopter-startup-delivers-tacos-by-unmanned-drone-helicopter_n_1375842
- [49] Gallucci, N. (2017). Doughnuts were just delivered by a drone. <https://mashable.com/2017/06/01/drone-delivering-doughnuts/#ReFFy35uPsqt>.
- [50] Staff, J. (2014). Happiness from the skies: Watch coke drones refresh guest workers in Singapore. <https://www.coca-colacompany.com/stories/happiness-from-the-sky-watch-coke-drones-refresh-guest-workers-in-singapore>.
- [51] <https://newsroom.dominos.com.au/media/2022/1/27/look-up-dominos-drone-delivery-trial-cleared-for-take-off-in-new-zealand>
- [52] Franco, M. (2016). DHL uses completely autonomous system to deliver consumer goods by drone. URL <http://newatlas.com/dhl-drone-delivery/43248/>.
- [53] <https://www.forbes.com/sites/jilliandonfro/2019/06/05/amazon-new-delivery-drone-remars-warehouse-robots-alexa-prediction/?sh=42faac76145f>
- [54] Rakuten (2019). Rakuten's New Island-Hopping Drone Delivery Service. <https://rakuten.today/blog/island-hopping-drone-delivery-service.html>.
- [55] <https://www.businessinsider.com/drone-delivery-startup-manna-adapted-to-coronavirus-pandemic-2020-5#:~:text=A%20tiny%20Irish%20drone%20startup,ancestral%20home%20of%20Barack%20Obama&text=Irish%20drone%2Ddelivery%20startup%20Manna,lockdown%20started%20to%20kick%20in>
- [56] Demuyakor, J. The impact of Zipline Drone Technology on Digital Emergency Health Delivery in Ghana. Shanlax Int. J. Arts Sci. Humanit. 2020, 8, 242–253.

- [57] Ackerman, E. & Strickland, E. (2018). Zipline expands its medical delivery drones across East Africa. <https://spectrum.ieee.org/aerospace/aviation/zipline-expands-itsmedical-delivery-drones-across-east-africa>.
- [58] Stewart, J. (2017). Blood-carrying, Life-saving Drones Take off for Tanzania. <https://www.wired.com/story/zipline-drone-delivery-tanzania>.
- [59] Baker, A. (2017). The American Drones Saving Lives in Rwanda. URL <http://time.com/rwanda-drones-zipline/>.
- [60] Landhuis, E. (2017). Tanzania gears up to become a Nation of Medical Drones. <https://www.npr.org/sections/goatsandsoda/2017/08/24/545589328/tanzaniagears-up-to-become-a-nation-of-medical-drones>.
- [61] Petrova, M. & Kolodny, L. (2018). Zipline's new drone can deliver medical supplies at 79 miles per hour. <https://www.cnn.com/2018/04/02/zipline-new-zip-2-dronedelivers-supplies-at-79-mph.html>.
- [62] Taylor, C. (2013). How Matternet Wants To Bring Drone Delivery To The People Who Need It Most. <https://techcrunch.com/2013/12/10/how-matternet-wants-to-bring-drone-delivery-to-the-people-who-need-it-most/>.
- [63] Škrinjar, J. P., Škorput, P., & Furdić, M. (2019). Application of unmanned aerial vehicles in logistic processes. In *New Technologies, Development and Application 4* (pp. 359-366). Springer International Publishing.
- [64] Rapson, D., & Muehlegger, E. (2023). Global transportation decarbonization. *Journal of Economic Perspectives*, 37(3), 163-188.
- [65] Schöder, D. (2017). *Technisch-wirtschaftliche Bewertung des Einsatzes von batterieelektrischen Nutzfahrzeugen in der Distribution von Konsumgütern*. Berlin: Universitätsverlag der TU Berlin, 2017.
- [66] <https://www.un.org/en/actnow/ten-actions>
- [67] Benarbia, T., & Kyamakya, K. (2021). A literature review of drone-based package delivery logistics systems and their implementation feasibility. *Sustainability*, 14(1), 360.
- [68] Chen, C., Demir, E., & Huang, Y. (2021). An adaptive large neighborhood search heuristic for the vehicle routing problem with time windows and delivery robots. *European journal of operational research*, 294(3), 1164-1180.
- [69] Bakach, I., Campbell, A. M., & Ehmke, J. F. (2021). A two-tier urban delivery network with robot-based deliveries. *Networks*, 78(4), 461-483.

- [70] Boysen, N., Schwerdfeger, S., & Weidinger, F. (2018). Scheduling last-mile deliveries with truck-based autonomous robots. *European Journal of Operational Research*, 271(3), 1085-1099.
- [71] Raghunatha, A., Lindkvist, E., Thollander, P., Hansson, E., & Jonsson, G. (2023). Critical assessment of emissions, costs, and time for last-mile goods delivery by drones versus trucks. *Scientific Reports*, 13(1), 11814.
- [72] Pugliese, L. D. P., Guerriero, F., & Macrina, G. (2020). Using drones for parcels delivery process. *Procedia Manufacturing*, 42, 488-497.
- [73] Doole, M., Ellerbroek, J., & Hoekstra, J. (2020). Estimation of traffic density from drone-based delivery in very low level urban airspace. *Journal of Air Transport Management*, 88, 101862.
- [74] Stolaroff, J. K., Samaras, C., O'Neill, E. R., Lubers, A., Mitchell, A. S., & Ceperley, D. (2018). Energy use and life cycle greenhouse gas emissions of drones for commercial package delivery. *Nature communications*, 9(1), 409.
- [75] Barr, S., & Gilg, A. (2006). Sustainable lifestyles: Framing environmental action in and around the home. *Geoforum*, 37(6), 906–920. <https://doi.org/10.1016/j.geoforum.2006.05.002>
- [76] Lee, J. S., Hsu, L. T., Han, H., & Kim, Y. (2010). Understanding how consumers view green hotels: How a hotel's green image can influence behavioural intentions. *Journal of Sustainable Tourism*, 18(7), 901–914. <https://doi.org/10.1080/09669581003777747>.
- [77] <https://www.viritopia.com/blog/green-brand-image-what-it-and-why-your-business-needsit#:~:text=What%20is%20a%20green%20brand,than%20their%20competitors'%20environmental%20measures>.
- [78] Hwang, J., & Kim, H. (2019). Consequences of a green image of drone food delivery services: The moderating role of gender and age. *Business Strategy and the Environment*, 28(5), 872-884.
- [79] Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. (2011). Willingness to pay for electric vehicles and their attributes. *Resource and energy economics*, 33(3), 686-705.
- [80] <https://www.elektrikport.com/haber-roportaj/elektrikli-arabalar-icten-yanmali-motorlu-araclara-gore-cevre-icin-daha-mi-zararli/22472#ad-image-0>
- [81] Cready, E., Lippert, J., Pihl, J., Weinstock, I., & Symons, P. (2003). Technical and economic feasibility of applying used EV batteries in stationary applications (No. SAND2002-4084).

- [82] Sandia National Lab.(SNL-NM), Albuquerque, NM (United States)
- [83] Sandia National Lab.(SNL-CA), Livermore, CA (United States)
- [84] Es Yurek, E. (2024). Impact of Drone Battery Recharging Policy on Overall Carbon Emissions: The Traveling Salesman Problem with Drone. *Drones*, 8(3), 108.
- [85] https://shura.org.tr/wp-content/uploads/2023/05/SHURA-2023-02-Rapor-Net-Sifir-2053_04052023.pdf
- [86] Breeze, P. (2017). *Electricity generation and the environment*. Academic Press.
- [87] Rabta, B., Wankmüller, C., & Reiner, G. (2018). A drone fleet model for last-mile distribution in disaster relief operations. *International Journal of Disaster Risk Reduction*, 28, 107-112.
- [88] Koiwanit, J. (2018). Analysis of environmental impacts of drone delivery on an online shopping system. *Advances in Climate Change Research*, 9(3), 201-207.
- [89] Lebeau, P., De Cauwer, C., Van Mierlo, J., Macharis, C., Verbeke, W., & Coosemans, T. (2015). Conventional, hybrid, or electric vehicles: which technology for an urban distribution centre?. *The Scientific World Journal*, 2015.
- [90] Balaban, M. A., Mastaglio, T. W., & Lynch, C. J. (2016, December). Analysis of future UAS-based delivery. In *2016 Winter Simulation Conference (WSC)* (pp. 1595-1606). IEEE.
- [91] Gruber, J., Kihm, A., & Lenz, B. (2014). A new vehicle for urban freight? An ex-ante evaluation of electric cargo bikes in courier services. *Research in Transportation Business & Management*, 11, 53-62.
- [92] Garg, V., Niranjana, S., Prybutok, V., Pohlen, T., & Gligor, D. (2023). Drones in last-mile delivery: A systematic review on Efficiency, Accessibility, and Sustainability. *Transportation Research Part D: Transport and Environment*, 123, 103831.
- [93] Moshref-Javadi, M., & Winkenbach, M. (2021). Applications and Research avenues for drone-based models in logistics: A classification and review. *Expert Systems with Applications*, 177, 114854.
- [94] Goodchild, A., & Toy, J. (2018). Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO2 emissions in the delivery service industry. *Transportation Research Part D: Transport and Environment*, 61, 58-67.
- [95] Hur, S. H., & Won, M. (2024). CO2 emissions and delivery time of last-mile drone delivery using trucks. *IET Intelligent Transport Systems*, 18(1), 101-113.

- [96] Lemardelé, C., Estrada, M., Pagès, L., & Bachofner, M. (2021). Potentialities of drones and ground autonomous delivery devices for last-mile logistics. *Transportation Research Part E: Logistics and Transportation Review*, 149, 102325.
- [97] Dukkanci, O., Kara, B. Y., & Bektaş, T. (2021). Minimizing energy and cost in range-limited drone deliveries with speed optimization. *Transportation Research Part C: Emerging Technologies*, 125, 102985.
- [98] Coindreau, M. A., Gallay, O., & Zufferey, N. (2021). Parcel delivery cost minimization with time window constraints using trucks and drones. *Networks*, 78(4), 400-420.
- [99] Park, J., Kim, S., & Suh, K. (2018). A comparative analysis of the environmental benefits of drone-based delivery services in urban and rural areas. *Sustainability*, 10(3), 888.
- [100] Gawron, J. H., Keoleian, G. A., De Kleine, R. D., Wallington, T. J., & Kim, H. C. (2018). Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects. *Environmental science & technology*, 52(5), 3249-3256.
- [101] Figliozzi, M. A. (2020). Carbon emissions reductions in last mile and grocery deliveries utilizing air and ground autonomous vehicles. *Transportation Research Part D: Transport and Environment*, 85, 102443.
- [102] Ehrler, V. C., Schöder, D., & Seidel, S. (2021). Challenges and perspectives for the use of electric vehicles for last mile logistics of grocery e-commerce—Findings from case studies in Germany. *Research in Transportation Economics*, 87, 100757.
- [103] Raghunatha, A., Lindkvist, E., Thollander, P., Hansson, E., & Jonsson, G. (2023). Critical assessment of emissions, costs, and time for last-mile goods delivery by drones versus trucks. *Scientific Reports*, 13(1), 11814.
- [104] Rodrigues, T. A., Patrikar, J., Oliveira, N. L., Matthews, H. S., Scherer, S., & Samaras, C. (2022). Drone flight data reveal energy and greenhouse gas emissions savings for very small package delivery. *Patterns*, 3(8).
- [105] Wygonik, E., & Goodchild, A. (2012). Evaluating the efficacy of shared-use vehicles for reducing greenhouse gas emissions: a US case study of grocery delivery. In *Journal of the Transportation Research Forum* (Vol. 51, No. 2, pp. 111-126).
- [106] Li, F., & Kunze, O. (2023). A comparative review of air drones (UAVs) and delivery bots (SUGVs) for automated last mile home delivery. *Logistics*, 7(2), 21.

- [107] Ma, H., Balthasar, F., Tait, N., Riera-Palou, X., & Harrison, A. (2012). A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy policy*, 44, 160-173.
- [108] Satiennam, T., Satiennam, W., Tankasem, P., Jantosut, P., Thengnamlee, J., & Khunpumphet, W. (2014). A study of potential electric motorcycle use to support a low carbon society: case of a developing Asian city. *Advanced Materials Research*, 931, 541-545.
- [109] Nocerino, R., Colorni, A., Lia, F., & Luè, A. (2016). E-bikes and E-scooters for smart logistics: environmental and economic sustainability in pro-E-bike Italian pilots. *Transportation research procedia*, 14, 2362-2371.
- [110] Hao, H., Cheng, X., Liu, Z., & Zhao, F. (2017). Electric vehicles for greenhouse gas reduction in China: A cost-effectiveness analysis. *Transportation Research Part D: Transport and Environment*, 56, 68-84
- [111] Ou, X., Yan, X., & Zhang, X. (2010). Using coal for transportation in China: Life cycle GHG of coal-based fuel and electric vehicle, and policy implications. *International Journal of Greenhouse Gas Control*, 4(5), 878-887.
- [112] Patella, S. M., Grazieschi, G., Gatta, V., Marcucci, E., & Carrese, S. (2020). The adoption of green vehicles in last mile logistics: A systematic review. *Sustainability*, 13(1), 6.
- [113] Oliveira, C. M. D., Albergaria De Mello Bandeira, R., Vasconcelos Goes, G., Schmitz Gonçalves, D. N., & D'Agosto, M. D. A. (2017). Sustainable vehicles-based alternatives in last mile distribution of urban freight transport: A systematic literature review. *Sustainability*, 9(8), 1324.
- [114] Edirimanne, R., Fernando, W. M., Nielsen, P., Perera, H. N., & Thibbotuwawa, A. (2024). OPTIMIZING UNMANNED AERIAL VEHICLE BASED FOOD DELIVERY THROUGH VEHICLE ROUTING PROBLEM: A COMPARATIVE ANALYSIS OF THREE DELIVERY SYSTEMS. *Applied Computer Science*, 20(1), 85-105.
- [115] Melo, S., & Baptista, P. (2017). Evaluating the impacts of using cargo cycles on urban logistics: Integrating traffic, environmental and operational boundaries. *European transport research review*, 9, 1-10.
- [116] Choi, Y., Schonfeld, P. M., Lee, Y. J., & Shin, H. S. (2021). Innovative methods for delivering fresh food to underserved populations. *Journal of Transportation Engineering, Part A: Systems*, 147(1), 04020140.

- [117] Chen, X., & Wang, X. (2016). Effects of carbon emission reduction policies on transportation mode selections with stochastic demand. *Transportation Research Part E: Logistics and Transportation Review*, 90, 196-205.
- [118] Delucchi, M. A., Yang, C., Burke, A. F., Ogden, J. M., Kurani, K., Kessler, J., & Sperling, D. (2014). An assessment of electric vehicles: technology, infrastructure requirements, greenhouse-gas emissions, petroleum use, material use, lifetime cost, consumer acceptance and policy initiatives. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 372(2006), 20120325.
- [119] Siragusa, C., Tumino, A., Mangiaracina, R., & Perego, A. (2022). Electric vehicles performing last-mile delivery in B2C e-commerce: An economic and environmental assessment. *International Journal of Sustainable Transportation*, 16(1), 22-33.
- [120] Zhao, R., Yang, L., Liang, X., Guo, Y., Lu, Y., Zhang, Y., & Ren, X. (2019). Last-mile travel mode choice: Data-mining hybrid with multiple attribute decision making. *Sustainability*, 11(23), 6733.
- [121] Boysen, N., Fedtke, S., & Schwerdfeger, S. (2021). Last-mile delivery concepts: a survey from an operational research perspective. *Or Spectrum*, 43(1), 1-58.
- [122] Fan, W., Xu, M., Dong, X., & Wei, H. (2017). Considerable environmental impact of the rapid development of China's express delivery industry. *Resources, Conservation and Recycling*, 126, 174-176.
- [123] Shahmohammadi, S., Steinmann, Z. J., Tambjerg, L., van Loon, P., King, J. H., & Huijbregts, M. A. (2020). Comparative greenhouse gas footprinting of online versus traditional shopping for fast-moving consumer goods: A stochastic approach. *Environmental science & technology*, 54(6), 3499-3509.
- [124] Van Loon, P., Deketele, L., Dewaele, J., McKinnon, A., & Rutherford, C. (2015). A comparative analysis of carbon emissions from online retailing of fast moving consumer goods. *Journal of Cleaner Production*, 106, 478-486.
- [125] Wang, X., Zhang, S., & Schneider, N. (2021). Evaluating the carbon emissions of alternative food provision systems: A comparative analysis of recipe box and supermarket equivalents. *Technological Forecasting and Social Change*, 173, 121099.
- [126] Atilgan, B., & Azapagic, A. (2015). Life cycle environmental impacts of electricity from fossil fuels in Turkey. *Journal of Cleaner Production*, 106, 555-564.

- [127] Gevaers, R., Van de Voorde, E., & Vanelander, T. (2014). Cost modelling and simulation of last-mile characteristics in an innovative B2C supply chain environment with implications on urban areas and cities. *Procedia-Social and Behavioral Sciences*, 125, 398-411.
- [128] Mathew, A. O., Jha, A. N., Lingappa, A. K., & Sinha, P. (2021). Attitude towards drone food delivery services—role of innovativeness, perceived risk, and green image. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(2), 144.
- [129] Hwang, J., Joo, K., & Moon, J. (2023). A study on behavioral intentions in the field of eco-friendly drone food delivery services: Focusing on demographic characteristics and past experiences. *Sustainability*, 15(7), 6253.
- [130] Merkert, R., Bliemer, M. C., & Fayyaz, M. (2022). Consumer preferences for innovative and traditional last-mile parcel delivery. *International Journal of Physical Distribution & Logistics Management*, 52(3), 261-284.
- [131] Namkung, Y., & Jang, S. (2017). Are consumers willing to pay more for green practices at restaurants?. *Journal of Hospitality & Tourism Research*, 41(3), 329-356.
- [132] Serrano-Hernandez, A., Ballano, A., & Faulin, J. (2021). Selecting freight transportation modes in last-mile urban distribution in pamplona (Spain): An option for drone delivery in smart cities. *Energies*, 14(16), 4748.
- [133] https://www.nufusu.com/ilce/saricam_adana-nufusu
- [134] <https://www.hondapowersportsoftroy.com/New-Inventory-2024-Honda-Motorcycle-Scooter-Super-Cub-C125-ABS-Honda-Powersports-of-Troy-13232783>
- [135] <https://www.lexmoto.com/models/ZN125T-K>
- [136] https://uavsystemsinternational.com/pages/heavy-lift-payload-drones?gad_source=1&gclid=CjwKCAjwgdayBhBQEiwAXhMxtgKQ2Qh1qa9m7PoTVvkbWdxRPQx0mRGNnDfWfclSLQOqoT7fRFlrthoCCIsQAvD_BwE
- [137] https://enerji.gov.tr/Media/Dizin/EVCED/tr/%C3%87evreVe%C4%B0klim/%C4%B0klimDe%C4%9Fi%C5%9Fikli%C4%9Fi/EmisyonFaktorleri/TEUVETN_Emisyon_Fakt%C3%B6rleri_Bilgi_Formu.pdf
- [138] <https://www.epdk.gov.tr/Detay/Icerik/3-1327/elektrik-faturalarina-esas-tarife-tablolari>
- [139] <https://www.futurelearn.com/info/courses/simulation-for-logistics-an-introduction/0/steps/66025>
- [140] <https://www.oit.va.gov/Services/TRM/ToolPage.aspx?tid=7430>

- [141] Allen, T. T., & Allen, T. T. (2011). Introduction to ARENA software. Introduction to Discrete Event Simulation and Agent-based Modeling: Voting Systems, Health Care, Military, and Manufacturing, 145-160.
- [142] <https://www.rockwellautomation.com/en-us/products/software/arena-simulation/discrete-event-modeling.html#:~:text=Arena%20Discrete%20Event%20Simulation%20Software%20features%3A&text=Statistical%20analysis%20and%20report%20generation,to%20visualize%20results%20beyond%20numbers>
- [143] <https://infotekas.com.tr/simulasyon-ve-modelleme.html#:~:text=Sim%3%BClasyon%2C%20teorik%20ya%20da%20ger%3%A7ek,izlenmesini%20sa%4%9Flayan%20bir%20modelleme%20tekni%C4%9Fidir>
- [144] https://ocw.metu.edu.tr/pluginfile.php/409/mod_resource/content/0/lecture13.pdf
- [145] <https://uh.edu/~lcr3600/simulation/steps.html>
- [146] Marzolla, M. (2005). Simulation-based performance modeling of UML software architectures (Doctoral dissertation, Ca'Foscari University of Venice, Italy).
- [147] Dağsuyu, C. (2013) Bozulabilen ürünler için miktar iskontolu optimum fiyat politikalarının belirlenmesi ve uygulaması (Master's thesis, Fen Bilimleri Enstitüsü).
- [148] Law, A.M. and Kelton, W.D. (1991) Simulation Modelling and Analysis. 2nd Edition, McGraw-Hill, New York.
- [149] AKCAN, S., 2010. Hastane Sistemlerinde Çoklu Malzeme Durumu İçin Simülasyon Meta-Modellemeye Dayalı Stok Optimizasyonu. Çukurova Üniversitesi Doktora Tezi, Adana, 174s.
- [150] FIELD, A., 2005. Discovering Statistics Using SPSS. Sage Publications, London, 779. Field, 2005.
- [151] Carson, Y., & Maria, A. (1997, December). Simulation optimization: methods and applications. In Proceedings of the 29th conference on Winter simulation (pp. 118-126).
- [152] https://literature.rockwellautomation.com/idc/groups/literature/documents/pp/aro-pt-pp001_-en-p.pdf
- [153] <https://karenrempel.com/wp-content/uploads/2009/11/arena-optquest-users-guide.pdf>
- [154] <https://robertsoczewica.medium.com/what-is-topsis-b05c50b3cd05>
- [155] Chakraborty, S. (2022). TOPSIS and Modified TOPSIS: A comparative analysis. Decision Analytics Journal, 2, 100021.

- [156] Özcan, E. C., Ünlüsoy, S., & Eren, T. (2017). A combined goal programming–AHP approach supported with TOPSIS for maintenance strategy selection in hydroelectric power plants. *Renewable and Sustainable Energy Reviews*, 78, 1410-1423.
- [157] Wang, L., Chu, J., & Wu, J. (2007). Selection of optimum maintenance strategies based on a fuzzy analytic hierarchy process. *International journal of production economics*, 107(1), 151-163.
- [158] Ertuğrul, İ., & Karakaşoğlu, N. (2009). Performance evaluation of Turkish cement firms with fuzzy analytic hierarchy process and TOPSIS methods. *Expert systems with applications*, 36(1), 702-715.)
- [159] Breeze, P. (2017). *Electricity generation and the environment*. Academic Press.

