ALIS: AGRICULTURAL LOGISTICS FOR INTELLIGENT SUSTAINABLE SYNCHROMODAL LOGISTIC

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B.S., Civil Engineering, Boğaziçi University, 2017

M.S., Civil Engineering, Boğaziçi University, 2020

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

Graduate Program in Civil Engineering

Boğaziçi University

2025

ACKNOWLEDGEMENTS

First and foremost, I wish to extend my deepest gratitude to my advisor, Prof. Ilgın Yaşar. Her mentorship and unwavering support throughout my doctoral studies have always been indispensable for me while conducting my research. With her guidance, this dissertation has reached a level of standard that I have never been able to imagine before. Her encouragement and ethusiasm have constantly made me push myself for better results. After working with her for three years as a graduate researcher and being her student for eight years, I can confidently say that her influence on my life, my career, and my character cannot be understated, and I will always be indebted to her.

I would like to thank the members of my dissertation committee, Prof. Muhammet Deveci for his valuable and endless support and guidance. I also wish to express my gratitude to Prof. Özer Çinicioğlu for his support and valueble feedback for this dissertation. Finally, I would like to thank Prof. Serhan Tanyel and Assist. Prof. Mehtap Işık for their valuable comments and suggestions.

I would also like to thank my parents, Filiz and Atilla Arsoy, who have supported me throughout my entire life. They have always provided me with the opportunities, encouragements, and their infinite love. I will always be forever indebted to them.

I also need to acknowledge the continuous support of my wife Seren Usta Arısoy. Many times that I have been frustrated with my progress, with her support and encouragements, I have been able to recover and get back to work.

Finally, I would like to thank Alperen Timuroğulları, my co-workers at Türkiye İş Bankası, Metro Türkiye Gross Market, and my countless friends for their continuous support during my academic studies.

ABSTRACT

ALIS: AGRICULTURAL LOGISTICS FOR INTELLIGENT SUSTAINABLE SYNCHROMODAL LOGISTIC

The journey of agricultural products from farm to fork is very important for ensuring the wellbeing of the people. Utilization of inefficient transportation modes and inefficient logistics systems can cause significant price hikes between the producer and the consumer which can jeopardize the food affordability and security. To address these issues, increasing the share of efficient and environmentally transportation modes, and designing innovative logistics strategy concepts are necessary. However, these tasks can be particularly challenging for countries with limited resources. Therefore, consideration of real-life constraints while designing these innovative concepts is essential. One of the most recent innovative logistics planning concept is called synchromodality which is a planning approach that aims to optimize the logistics operations and providing economic, environmental and sustainability benefits. This is achieved through searching for the optimum transportation route using real-time data that is being provided by all stakeholders of the logistics network. However, when discussed with logistics sector experts, the concept is often considered as vague and very difficult to implement in practice. In this dissertation, a new definition for the concept of synchromodality is presented and a model has been proposed based on this new definition. The proposed model that utilizes trucks for short distance trips and freight trains for long distance trips, is tested in an open-source simulation environment. 2 baseline and 4 proposed model alternatives are tested across a total of 792 scenarios. According to the results, the proposed model can reduce the fuel consumption levels significantly but comes with a trade-off in transportation duration. The new definition for the synchromodality is validated through the results of this use-case study and interviews with logistics experts.

ÖZET

ALIS: TARIM LOJİSTİĞİ İÇİN AKILLI SÜRDÜRÜLEBİLİR SENKROMODAL LOJİSTİK

Tarım ürünlerinin tarladan çatala olan yolculuğu, toplumun refahı için çok önemlidir. Verimsiz taşıma modlarının ve lojistik sistemlerinin kullanılması, üretici ile tüketici arasında önemli fiyat artışlarına neden olabilir ve ayrıca gıda erişilebilirliği ve güvenliği riskleri yaratabilir. Bu sorunlara çözüm olarak verimli ve çevre dostu taşıma modlarının payının artırılması ve inovatif lojistik stratejisi konseptlerinin tasarlanması gerekmektedir. Ancak, bu çözümlerin uygulanması sınırlı kaynaklara sahip ülkeler için özellikle zorlayıcı olabilir. Bu nedenle, bu yenilikçi çözümler tasarlanırken gerçek hayattaki kısıtlamalar mutlaka dikkate alınmalıdır. En yeni inovatif lojistik planlama konseptlerinden birisi senkromodal taşımacılık konseptidir. Bu konsepte göre lojistik ağının tüm paydaşları tarafından sağlanan gerçek zamanlı verilerle yapılan planlamalar, lojistik operasyonları optimize etmeyi ve ekonomik, çevresel ve sürdürülebilirlik faydaları sağlamayı hedeflemektedir. Ancak, lojistik sektörü uzmanlarıyla yapılan görüşmelere göre, bu konsept genellikle belirsiz ve pratikte uygulanması neredeyse imkansız olarak kabul edilmektedir. Bu doktora tezinde, senkromodalite kavramı için yeni bir tanım sunuldu ve bu yeni tanıma dayalı bir lojistik modeli önerildi. Kısa mesafe taşımacılık için kamyonların ve uzun mesafe taşımacılık için yük trenlerinin kullanılmasının önerildiği bu model, açık kaynaklı bir simülasyon ortamında test edilmiştir. Toplam 792 senaryoda 2 temel ve 4 önerilen model alternatifi test edilmiştir. Sonuçlara göre, önerilen model yakıt tüketim seviyelerini kayda değer ölçüde azaltabilirmektedir. Öncelikle dayanıklı gıda ürünleri için önerilen bu model, lojistik uzmanları ile değerlendirildiğinde hala geçerli bir seçenek olarak kabul edilmektedir. Senkromodalite için geliştirilen yeni tanım, önerilen modelin testlernin sonuçları ve lojistik uzmanlarıyla yapılan görüşmeler yoluyla doğrulanmıştır.

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LIST OF SYMBOLS

$accel$	Maximum acceleration
D	Number of diesel vehicles in the simulation
$decel$	Maximum deceleration
E	Number of electric vehicles in the simulation
E_{diesel}	Equivalent diesel fuel energy for a diesel freight train
E_{diesel_J}	Energy generated with diesel fuel consumption in joules
$E_{electric}$	Total Electric consumption of electric vehicle in watt-hours
$E_{mechanical}$	Mechanical energy required for the given vehicle's trip
J	Joules
$maxSpeed$	Maximum allowed speed minGap Minimum headway distance
ml_d	Diesel fuel consumption of d^{th} diesel fuel vehicle in milliliters
$vClass$	Vehicle class
$V_{diesel_{ml}}$	Diesel fuel consumption of diesel vehicle in milliliters
Wh_e	Electric consumption of eth electric vehicle in watt-hours
σ	Driver Imperfection Level of the Krauss Car-Following Model
η_{diesel}	Diesel motor efficiency
$\eta_{electric}$	Electric motor efficiency

LIST OF ACRONYMS/ABBREVIATIONS

3PL	Third Party Logistics
AI	Artificial Intelligence
AV	Autonomous Vehicles
CSF	Critical Success Factors
EPAct	Energy Policy Act
EU	European Union
FEU	40-ft Standard Container
GA	Genetic Algorithm
GGE	Gasoline-Galon-Equivalent
GHG	Greenhouse Gas
HBEFA	Handbook of Emission Factors for Road Transport
HDV-D-EU0	Diesel Driven Heavy Duty Vehicle Euro Norm 0
IoT	Internet of Things
ML	Machine Learning
OD	Origin-Destination
RegTech	Regulatory Technologies
SUMO	Simulation of Urban Mobility
TC	Republic of Türkiye
TraCI	Traffic Control Interface
UK	United Kingdom
US	United States

1. INTRODUCTION

1.1. Introduction and Background

Agricultural products are among the most critical goods for ensuring the well-being of a nation's population. In order to minimize the price gap between producers and consumers, it is essential to maintain low logistics costs. Without optimizing the logistics operations drastic price hikes of these products can be experienced. For example, in TC the price difference between producer and the market of a product can be up to approximately 600% or even more (Table 1.1). Many countries throughout the globe have developed their food logistics operations to a functional level. However, when the World Health Organization declared a global pandemic in March 2020, large scale disruptions exposed significant shortcomings in logistical infrastructure. Restricted worker mobility, abrupt shifts in consumer demand, and the closure of production facilities are some of the issues that must be resolved by the sector experts [1]. Furthermore, import-export restrictions, and other economic and geopolitical pressures, present additional issues for the logistics systems.

Table 1.1. Price differences between the producer and consumer in the last 12 months in TC collected from the website of Chairman of the Union of Turkish Chambers of Agriculture [2].

Date	**Product**	**Farm-Bazaar Price Difference (%)**	**Farm-Market Price Difference (%)**
2025-03	Haricot Bean	140.31	208.00
2025-02	Lemon	486.80	634.40
2025-01	Lemon	420.80	597.40
2024-12	Lemon	241.10	312.30
2024-11	Lemon	218.18	253.70
2024-10	Cauliflower	340.00	368.50
2024-09	Carrot	209.33	249.00
2024-08	Lemon	287.94	370.40
2024-07	Carrot	330.50	420.50
2024-06	Cherry	121.06	303.98
2024-05	Dry Figs	247.83	293.90
2024-04	Dry Figs	182.61	284.30

Fluctuation of oil prices is one of the most significant risks for the logistics sector in terms of economic risks, due to the fact fuel cost comprises more than 50% of the total operating cost [3]. The COVID-19 pandemic and the current geopolitical tensions cause significant volatility for the oil prices. It is unlikely that these tensions will not be resolved anytime soon, which indicates that the risk of fluctuating oil prices will be present for some time. Countries that have built up their logistics infrastructure not resilient to these price hikes will face serious challenges. Developing countries where road transportation holds a significant share of the logistics operations are the most vulnerable against this problem. Even though transportation via trucks have significant benefits in terms of flexible scheduling, they are also more expensive than rail transportation especially for long distance operations [4]. Therefore, policymakers and sector professionals are researching new and innovative approaches for shifting freight transportation operation towards more sustainable and efficient modes, such as railroad systems and electric heavy vehicles (i.e., trucks, trailers). On top of shifting towards these eco-friendly and efficient transportation modes, improving the logistics planning and operations is essential for better results, such as changing the OD points of the agri-food products' journey (Figure 1.1). When developing these new approaches and systems, it is essential to consider both environmental and sustainability aspects in addition to financial aspects. This is especially important for developing countries with significant trade volumes with EU nations such as TC. Considering these aspects may prevent or reduce the costs of future carbon import taxes outlined in the European Green Deal [5].

In 2023, the transportation sector was the second-largest source of CO2 emissions [6]. Approximately 40% of this emission is due to the freight transport operations [7]. According to the International Energy Agency railroad mode is one of the most energy-efficient and sustainable modes of transportation. Globally, railroad logistics operations contribute approximately 0.3% to total carbon emissions [8]. However, a significant percentage of all global logistics operations is being conducted by road transportation vehicles [9]. As a part of the EU's zero net emission strategy, one of the key objectives is to shift the freight transportation towards railroad network for

distances over 350km [10]. The main advantages of road transportation modes are flexible scheduling and being cost-efficient for short distances. On the other hand, when long distance transportation is considered, the operation costs increase rapidly, compared to railroad operations [11]. In order to maximize the benefits from these different modes of transportation, the integration must be done in a way that it creates a logistics system that is fast, reliable and safe [12]. Additionally, by improving the integration with railroad networks and increasing its share in the logistics operations, a significant step will be taken towards achieving the net-zero emission levels [13].

Figure 1.1. A train station that is being utilized as a food marketplace.

The main purpose of this research is to investigate the effect of railroad and road logistics operation integration under various scenarios. The objective is to minimize the price hike between the producer (i.e., farm) and the consumer (i.e., fork) due to the transportation costs. In this scope a transportation simulation tool, namely SUMO is used [14]. A synthetic network is built in this simulation environment. The proposed system, scenarios, assumptions, key parameters for tuning and testing are presented in Section 4. The system is based on the proposed definition of the synchromodality concept that has been presented in Section 5. Detailed information about this innovative concept is presented under Section 3. The results of this study are expected to make a significant contribution for evaluating the benefits of proper integration, proposing an infrastructural investment that is applicable for developing countries with limited resources, and defining the concept of synchromodality in terms of sustainability aspect.

2. PROBLEM DEFINITION

During the farm-to-fork journey, significant price increases occur due to various factors. In the current state, the majority of these trips are conducted with diesel fuel trucks for both long and short distance trips, which is neither cost-efficient nor environmentally friendly. Logistics expenses and the intermediaries that are involved throughout the food supply-chain are some of the most important contributors for this price hike. This price increase is a critical issue for both the producers and the consumers, which is not sustainable.

In order to solve this issue, sustainable and eco-friendly transportation strategies must be adopted. Railroad systems provide efficient and high-capacity transportation solutions, which especially beneficial for long-distance trips. Furthermore, significant benefits, in terms of supporting the efforts against climate change by shifting towards rail transportation, can be obtained. Road transportation has the advantage of flexible planning capability, which can be useful for short distance frequent trips. In summary, the strengths of each transportation mode must be optimally utilized according to the trip characteristics.

2.1. Goals and Objectives

The goal of this dissertation is to design alternative logistics strategies that prioritizes sustainable and efficient transportation modes and evaluate the performance of these proposed methods. To achieve this goal the following objectives must be completed:

(i) Construct a simulation environment in the SUMO tool for testing the proposed logistics strategy alternatives,
(ii) Define simulation parameters and the value ranges of these parameters to create different simulation scenarios,

(iii) Evaluate and compare the simulation outputs of these logistics strategies that are more efficient, eco-friendly, and sustainable, under different scenarios, and provide insights for the logistics sector experts.

2.2. Motivation of Dissertation

Food products generally have low price-elasticity. This causes the impact of the food inflation to be amplified. As the price increase between farm and consumer, food products become much more difficult to afford. Simultaneously, the price hikes that do not benefit the producers increase the risk of decreased agricultural productivity. Therefore, designing food logistics strategies that are sustainable, economically efficient, and beneficial for both consumers and producers is essential.

The dependence on road transportation via trucks is an economically inefficient and environmentally unsustainable strategy. It is important to develop strategies that utilizes the unique advantages of each transportation mode. These strategies must be optimized according to specific trip characteristics. In addition to economic considerations, environmental impact of the logistics operations must be considered. The potential emission taxes that may be implemented in the future is one of the main factors behind this motivation. In summary, the proposed logistics strategies must address the economic efficiency, environmental impact and level of sustainability.

2.3. Scope of Dissertation

In this dissertation the main focus is on developing different strategies that prioritize different transportation modes (e.g. diesel trucks and freight trains, and electric trucks and freight trains). These alternatives are tested in a semi-synthetic simulation environment. In this environment a simple network is designed. With this approach it is possible to compare the performances of different alternatives in a clear manner.

Logistics operations between the producers and consumers are the main focus of the simulations. Intermediate stages, such as inventory management, warehousing and optimization of vehicle availability, are not analyzed in detail. These stages are handled with assumptions that are collected by discussing with sector experts and literature reviews. Additionally, influence of weather, geography, road network geometry and other external factors on the performance of alternatives are not covered in this research.

Different alternatives are tested under various scenarios. By changing the road network, vehicle properties, and logistics operations parameters between certain ranges these scenarios are created. However, some of the parameters that are defined in this simulation environment are collected from other studies in the literature and interviews with logistics sector experts.

For the simulation tool, SUMO which is an open-source traffic simulation package is utilized [14]. In order to control and edit the running traffic simulation TraCI and Libsumo packages are utilized. The simulation code is written in Python syntax. With these packages, it is possible to dynamically control the simulation and collect detailed simulation results.

2.4. Contributions of Dissertation

With this dissertation the following contributions are provided to the subject of sustainable food logistics systems:

- A new logistics strategy that focuses on food transportation is proposed. The proposed system combines road (e.g. trucks) and railroad systems (e.g. freight trains) and tests both fossil fuel and electric variations of these vehicles in order to maximize efficiency and minimize the climate change effect. The train stations are conceptualized as food marketplaces. By doing so that the need of an additional last-mile trip is eliminated. Instead, the products that are transported via

freight trains are directly delivered to supermarkets or warehouses. Additionally, a sensitivity analysis is conducted in order to evaluate the proposed alternatives' performance under different conditions.

- A definition for the concept of "Synchromodality" is presented. As explained in later sections, a universally accepted definition for this concept is not available in the literature. Furthermore, the available definitions are considered as abstract or difficult to implement in real-life. With the experiments that are conducted in this dissertation and the policy implications according to the experiment results, a new definition that is considered as acceptable by sector experts is presented.
- According to the literature review, most of the logistics simulation works are done with commercial or non-traffic-specific simulation tools. The number of logistics simulations studies that are conducted in SUMO environment is very limited and utilization of electric vehicles, such as electric freight trains and electric cargo trucks, is almost zero. Available logistics modeling studies in the literature that do utilize SUMO often lack detailed methodologies such as vehicle and network parameters which prevents replication. In this dissertation, the simulation parameters that are important for modelling these electric vehicle types within SUMO are explicitly presented and can be utilized in future logistics studies.

2.5. Organization of Dissertation

In section 3, the literature review is presented. Studies from the literature and practice about synchromodality concept, technological developments in the agricultural logistics field, logistics modeling, and last-mile delivery systems are presented. In section 4, the methodology of the dissertation is explained. The proposed model is introduced and the case study for testing this model is presented. Results of the proposed model for different test scenarios are available under this section. In section 5, the policy implications of the proposed model and its performance is investigated. A new definition for the concept of synchromodality is presented under this section. In section 6, conclusion and final comments are presented.

3. LITERATURE REVIEW

The literature review is presented in this section. Studies about synchromodality, traffic modeling, last mile delivery with railroad systems, and technological developments in the logistics sector have been investigated. According to the research in the literature, not enough focus is given to the subject of railroad prioritized food logistics. Especially after the COVID-19 pandemic, the focus must shift towards sustainable logistics operations, in terms of economic and environmental costs.

3.1. Synchromodality

Synchromodality is a planning approach for optimizing the logistics operations by searching for the optimum transportation path, whether by road, rail, air, or sea, using real time data and harmonious actions of stakeholders in the logistics network. By maximizing operational efficiency in terms of financial and environmental costs, the sustainability of the logistics system is expected to increase. Many studies in the literature are trying to find ways to utilize this concept and improve the performance of the logistics operations. A study has proposed an adaptation framework for synchromodal transport that can handle different scenarios of disturbances and disruptions [15]. According to the results, introducing the event severity information to the framework can improve the performance of the system. In a different study, a model-based decision support system is developed [16]. Enabled by synchromodality and synergy of passenger-freight mobility, the proposed system aims to increase the sustainability of the cities by reducing the logistics operations' impact and carbon emission levels. The system that is based on the hyperconnectivity principles can provide benefits up to 91% in terms of decreased impact of logistics operations on the time and space of the transportation network of the city. Using an agent-based modeling approach, a numerical experiment is conducted in another study [17]. According to the results synchromodal scenarios significant environmental and economic benefits can be obtained. Further benefits can also be gained if the stakeholders of the logistics system collaborate with

each other. In another simulation study a synchromodal planning algorithm is developed and implemented for a fourth-party logistics service provider in Netherlands [18]. Results of this study show that with this approach reduction in terms of both average cost and carbon emission can be obtained. Although many simulation studies exist, significant macro-traffic simulation research is lacking, highlighting a major gap in the field. One key shortcoming is the underutilization of open-source traffic simulation tools (i.e., SUMO).

Even though synchromodal transportation is very promising, there are also significant disadvantages and barriers to its real-life implementation. Lack of trust between stakeholders, technical difficulties that occur due to last minute changes, and privacy of stakeholders' data are some of the main concerns for this concept [19]. Additionally, insufficient incentives, regulations and infrastructure are critical issues for the stakeholders [20]. The willingness for cooperation of the stakeholders is one of the main aspects that planners must take into consideration if they desire to utilize synchromodal planning approach [21]. A central authority should set standards and regulations by collaborating with logistics stakeholders, ensure data security, and improve the infrastructure to shift logistics companies towards sustainable and efficient transport modes like rail systems. However, a major obstacle is the lack of a concrete and universal definition of synchromodality [22]. This obstacle is also one of the reasons behind the lack of trust between logistics system's stakeholders.

There is a significant need for clear definitions so that further research and real-life implementations can be conducted. The differing definitions among various system players cause inconsistencies and, consequently, a lack of trust among them. In some studies, the real-time data aspect is primarily focused [17, 23]. Collaboration between the stakeholders is also focused, especially with the utilization of information sharing [24]. Other studies emphasize on the flexibility and responsiveness aspect [25]. The insufficient development of supporting infrastructure for synchromodality is partially a consequence of the conceptual ambiguity existing in the literature regarding its infrastructural needs. To fully realize its potential, a more holistic approach must be

adopted in future definitions and frameworks. The necessary physical and technological infrastructure should be explicitly addressed [26].

As a result of this literature review there is a gap of clear definition that focuses on the sustainability aspect. Additionally, this definition should consider the specific context of developed versus developing countries. This gap is addressed in this study by proposing a new definition that acknowledges these distinctions. Researchers and industry professionals will be able to make more informed and effective plans in the field of sustainability through this definition. Additionally, policymakers can use this definition for planning infrastructural investments and allocation of resources. This will contribute to ensuring that these decisions are in harmony with their country's specific needs and level of development.

3.2. Technological Developments in Agricultural Logistics

Technological advancements have significantly advanced the field of agricultural logistics, with the integration of AI, blockchain technology, big data analytics, and robotics expected to further enhance the efficiency and security of logistics systems. However, when the applicability of these developments is inspected the available resource of the country becomes a significant factor. In the following subsections the state of different aspects of technological developments are investigated.

3.2.1. Digitalization in Agricultural Logistics

During and after COVID-19 the amount of collected data in the logistics sector has increased significantly [27, 28]. AI can utilize this data to optimize logistics routes, enable autonomous vehicle deliveries, and enhance supply chain management [29].

A wide range of studies in the literature focus on applying AI to enhance logistics systems' performance. Other studies investigate the difficulties in integrating AI into logistics operations and how to address these challenges. Additionally, several studies

investigate the critical factors necessary for the successful integration of AI into logistics systems.

To ensure the reliability of AI methodologies, data transparency and integrity are essential [30]. Similarly, logistics approaches that depend on information sharing, such as synchromodality, require transparent and reliable data [21]. Identifying CSFs that enhance information sharing and data transparency is, therefore, a crucial area of investigation. A study conducted in Vietnam explored these CSFs within the context of agricultural logistics [31]. According to the results, policymakers and sector professionals must focus on technology, organization, regulatory and economic aspects. By improving the hardware and software infrastructure for collecting and processing data in a reliable manner, identifying cooperation opportunities, understanding regulation's role, and managing the budget and scalability, the efficiency and transparency of data sharing can improve significantly. A different study has identified several critical factors for adopting AI in the food supply chain: technological preparedness, data privacy and security measures, satisfaction of customer, perceived benefits, demand fluctuation, regulatory compliance, competition pressure, and effective information sharing among partners [32]. Policymakers and sector professionals must realize these factors in order to optimize the performance of logistics operations. In a study the potential of combining information sharing and AI is researched. The results show that combining information sharing and AI can result in decreased levels of carbon emission and financial costs by 13% and 21% respectively [33]. By optimizing the overall transportation operations, the total cost of transportation cost has approximately decreased by 13%, which is a significant benefit for especially developing countries with limited resources. While AI is mainly used for increasing the efficiency of the implemented system, other digital technologies provide benefits from different aspects such as data privacy and transparency.

Blockchain is a beneficial technology for AI in terms of archiving data in a transparent and traceable manner [34]. It enables supply chain monitoring in real-time and provides a safe and fair environment for information sharing [35]. As an example of

utilization of blockchain technology in the supply chain management domain, the company AgriDigital has successfully completed the transaction of 23.46 tons of grain on a blockchain in the December of 2016 [36]. Since this operation, the transaction of 1.6 million tons of grain has been completed which indicates the potential of this technology. Another company called Louis Dreyfus Co. aims to reduce the required time for document processing by 80% through matching data in real time automatically, eliminating double checks and accidental duplications [37]. In another study, a food supply chain traceability system is developed for China. In this system the blockchain technology is combined with Radio-Frequency Identification technology. The end results show that by utilizing these technologies, it is possible to store and share the original agri-food production, processing, storage operations, logistics, and selling links [38]. All of these developments are indications for the potential of utilization of blockchain technology for compensating the lack of trust between parties of the logistics stakeholders for information sharing. The optimization capabilities of AI and ML technologies and storing and sharing data in a reliable manner with blockchain calls the need for other technological advancements so that these outputs can be transferred from anywhere to anywhere in a fast and safe manner.

New connection technologies such as 5G and 6G are presenting significant potential for improving the collection and sharing of critical data for production and distribution of agricultural products. With the advantages provided by 5G connectivity, information management systems can operate faster and in a more efficient manner which enhance supply chain coordination and enabling real-time decision-making [39]. Digital Twins is a technology that can benefit from these fast speeds of data transfer to create a reliable platform for experts' decision-making processes [40]. In a study, a solution that integrates 6G IoT technology, ML and blockchain is developed for predicting inbound logistics tasks and facilitating efficient communication between different parties of the logistics operations [41]. The field of AVs is another area that 5G connectivity can improve [42]. Farmers can utilize AVs to transport their food products over short distances to the nearest warehouses or to logistics centers where trains or trucks are ready for long-distance transportation. In urban areas the benefits of 5G

connectivity can be realized much easier. However, areas where agricultural production and transportation take place are much more rural and geographically challenging to implement this technology. By combining 5G towers and satellites that support this connection type must be used in a combined manner for being able to cover non-urbanized areas that a large portion of the logistics operations take place. According to a study, by employing this combined approach satisfies the key performance indicators of standard network availability requirements (latency, downlink throughput and uplink throughput) for different use-cases, including real-time tracking of animal transport [43]. A systematic literature review that focuses on the application of 5G technologies in the logistics sector reveals that there are a limited number of applications that utilizes 5G connection technology [44]. According to the results the limited use of 5G technology within the logistics sector is mainly due to the level of complexity of integrating this advanced technology, high initial investment costs, and the requirement for specialized training for employees. Considering the fact that the available resources for integrating 5G connection is far less for developing countries compared to developed countries, it can be expected that these limitations will continue for a foreseeable future for developing countries.

3.2.2. Data Management for Logistics

The importance of data and data-driven decision-making approaches are being realized in many different sectors [27]. With technological developments the amount of collected data and its collection speed are increasing every moment. This situation creates new challenges for interpreting and archiving the collected data in a structured and efficient manner. There are studies in the literature that focus on the key requirements, challenges and potential of proper data management.

According to a study, some key requirements for efficient data management implementation are collaborative data sharing and standardized information flow design among all parties of the supply chain. Additionally, in order to assure the quality of the gathered data, the irrelevant and low-quality data must be eliminated in a sys-

tematic manner [45]. Some other challenges that need to be resolved for realizing the complete benefits of data management applications are scalability, governance, and variety. Some of the potential solutions to overcome these challenges are distributed computing, cloud technology, data quality management applications, integration tools and platforms [137]. By utilizing these solutions, new technologies for data management and tools that make use of data management can be integrated to real-life logistics operations.

Smart vehicles are one of these emerging technologies that is expected to have a significant share in the supply chain operations. These vehicles can generate and share significant amount of data with their sensor and connection technologies [46]. Data management approaches can also benefit railroad transport as well. Sharing the scheduling, capacity and route information with efficient data management tools in a seamless manner can optimize multimodal transport operations, such as highway-railway transport [47]. Government authorities and sector professionals are working on developing sustainable and efficient policies for assuring the quality and compliance of data. One technology that can be utilized for these compliance processes is called RegTech [48]. RegTech enables efficient management of critical aspects of logistics operations such as driver compliance, shipment tracking, international payments, and documentation handling. In another study a role named data stewards is explained [49]. They are responsible for maintaining the quality and usability of the data so that a proper foundation is provided for the professionals and their decision-making processes. This role is also responsible for the reliability and compliance of the data by maintaining data standards that satisfies data protection laws. Companies, such as Walmart, are making use of these data management approaches and are obtaining benefits such as lower carrying costs and higher customer satisfaction levels [50].

It is possible for companies and policymakers to make data-driven informed decisions by utilizing data management technologies and approaches. There are many different opportunities that these generated data can be used in many different ways. However, it is also apparent that without having a standard for the collected data, in

terms of their structure and level of quality, it is very difficult to obtain meaningful insight for people to make data-driven effective decisions.

3.3. Logistics Modelling

Logistics simulation is mostly utilized for planning, operation and optimization processes. Agent-based simulations is one of the most common simulations approaches available. With this approach, it is possible to observe the highly detailed insights such as the interaction of logistics system agents between each other and with the constructed simulation environment [51]. It is also possible to evaluate the proposed system outputs based on the large amount of data generated at the end of the simulation.

Agricultural supply chain management is a very challenging domain. Factors that influence the planning phase of the logistics operations such as food quality, safety, and weather conditions, are what sets this domain apart from the other types of logistics operations [52, 53]. Therefore, latest technologies such as IoT, digital twins, etc., must be made use of in order to improve the efficiency of the logistics operations by logistics experts and policymakers. By doing so technological, organizational and environmental benefits can be obtained [54]. In the literature many different studies that employ different approaches for improving agri-food supply chain are available.

In a study that focuses on agri-food logistics optimization, Value Stream Mapping and simulation modeling are utilized [55]. The inefficiencies and sustainable improvement opportunities are identified in the supply-chain. According to the results the optimization implementations can provide significant economic benefits, such as a 3-year payback period and a success rate of up to 80%. In a different study an asymmetric evolutionary game model using multi-agent simulation approach is developed on the NetLogo platform [56]. The interactions between agricultural stakeholders, third-party logistics, and financial institutions are the main focus of that study. Under different revenue conditions, the results of the study present solutions that lead to stable and

mutually beneficial outcomes. These outcomes support the development of financial warehousing systems. Fuel cost is another aspect that is crucial for the logistics sector. In a study that focuses on fuel cost optimization for agricultural logistics, a new metaheuristic approach, named variable neighborhood strategy adaptive search, for solving the location and routing problem is proposed [57]. Compared to traditional optimization solutions, the proposed system is much more efficient in terms of computation duration, detecting optimum procurement hub locations and logistics routes. Testing across different operational scales shows that the obtained benefits are even more significant for medium and large-scale scenarios. The outcome of this research offers a practical solution for solving the cost and pricing challenges faced by the farmers. While these solutions provide beneficial solutions, the practical applicability of the proposed solutions must also be discussed with actual logistics experts for validation.

Electric vehicles in logistics provide new challenges that need to be resolved. In a study that addresses this subject, an electric vehicle location routing problem is modeled [58]. The results show that by integrating the warehouse location and route planning under distance constraints the constructed enhanced adaptive large neighborhood search algorithm provides better results than traditional exact methods. Another research focuses on the distribution challenges of perishable food products [59]. The developed solution focuses on minimizing the delivery costs and preservation of the freshness of the products. Energy efficient wireless vehicles are utilized. An improved ant colony algorithm for open vehicle routing is adapted which provides better performance compared to standard ant colony approaches. In a different study, the performance of fossil fuel and electric vehicles are compared under the scope of logistics path planning [60]. An improved version of the GA for optimizing the planning is developed. The results show that with this version of GA provides better results in terms of cost efficiency and carbon emission reduction. However, the fossil fuel vehicles are considered to be more advantageous for short distance trips compared to electric vehicles in terms of economic benefits due to fixed and maintenance costs. On the contrary the electric vehicles are much more beneficial for the environmental aspect. In another study that focuses on the electrification strategies in UK the preliminary

results of an agent-based modeling study are presented [61]. When evaluating the electrified vehicles for long haul logistics operations, it is observed that with electric trailers the fuel consumption rates decrease significantly.

Simulating and modeling logistics operations with railroad transportation are also a subject that is focused in many different studies in the literature. In a study, the efficiency of exporting operations of grain in Ukraine with railway transportation is investigated [62]. Using clustering approaches and multicriteria optimization techniques, junctions for loading the grains to be exported are identified. This solution provides a reduction in wagon turnaround cycles and logistics costs with decreased required fleet sizes. In another research, the shift in US grain transportation from traditional railroad services with grain elevators to shuttle train services with terminal grain elevators [63]. Three models are developed to evaluate logistics duration, cost and rail network capacity. The findings of this study show that with the proposed system, benefits in terms of speed, reliability, cost, and global competitiveness in the field of grain exports can be obtained. It is also emphasized that continuous investments in smart infrastructure are required in order to maintain the gained benefits. For future infrastructural planning, global food demand, technological developments, and shifts in rail traffic must be considered as well. In another study for grain logistics in the scope of global supply chains, a multi-criteria optimization model is formulated [64]. The model is evaluated for a multimodal global supply chain with road, rail and maritime transportation. An agent-based discrete-event simulation is conducted and delivery times, vehicle utilization, and infrastructure capacity usage are evaluated. After determining optimal fleet sizes, shipping routes, balanced load factors, the average delivery duration is observed as 6.5 hours by road and 83 hours by rail transport. According to the results at transfer points grain elevators and seaport terminals have to be improved in order to optimize the transfer between modes.

Many different approaches, concepts, and systems are evaluated in various simulation environments. However, there is a significant lack of studies that are conducted with simulation tools that are specialized for traffic simulation, such as SUMO [51,

65, 66, 67, 68]. The available studies that do utilize SUMO include very little detail about their methodologies, such as vehicle properties, network construction, and vehicle behavior. Most of the studies do not explicitly share these crucial values for replicating their work. This dissertation aims to address these gaps. As a contribution, the crucial simulation parameters for modeling are explicitly presented that allows the reproduction of these simulation runs. These values can be utilized in future logistics research.

3.4. Last-Mile Delivery Systems

The last mile delivery covers the part of the transportation operation between the transportation center and the destination. Additionally, first mile delivery indicates the part between the trip origin and transportation center [69]. Majority of these deliveries are done with road transportation [70]. With the increase of urban population, e-commerce development and the need for sustainable delivery systems the topic of last-mile delivery systems' importance has increased significantly. According to a literature review study, study five themes can be defined for this topic: emerging technologies and trends, optimization of logistics operations, supply chain structure, evaluation of the performance, and policies and regulations [71]. However, there is a significant lack of studies that considers the topic of last-mile delivery of perishable goods.

One of the biggest efficiency issues of the current supply chain systems is that the logistics vehicles travel with half their capacity in terms of cargo load. In US, trailers operate around 60% capacity, which is considerably higher than global average [72]. One of the main reasons of this inefficiency is that there is no centralized hub for coordinating the distribution of these trucks and trailers. Most companies have their own private facilities. Large retailers especially invest in their own private logistics operations. However, smaller companies are converting to use 3PL. These 3PLs allow multiple parties to utilize the same supply chain facilities which provides reduced financial and environmental costs. One of the benefits of these 3PLs is that they reduce the time share that the logistics operation vehicles travel without any cargo. In a study the

reduction of inefficient times by utilizing autonomous electric vehicles for transporting both food products and human travelers is focused on [73]. A GA based optimization framework is proposed to handle the transportation operations, such as trip demand handling, delays and product availability variations. According to the performance evaluations an improvement of transportation efficiency up to 78% is obtained and the delivery quality is doubled with this approach. Another study a physical internet architecture for fresh food distribution networks is proposed [74]. A freshness metric is designed to determine the delivery requirements. Based on these requirements loading/unloading processes onto trucks are planned. According to multiple simulations the proposed framework improves the food delivery freshness by 5%. Additionally, the driver's duration of being away from their homes decreased by 93%. In addition to designing frameworks, utilization of innovative vehicles that have the latest technology is another sub-topic of the last-mile delivery topic.

Electric vehicles have significant environmental benefits. Especially in urban settings, these types of vehicles have the most potential due to their range and the requirement of adequate infrastructure [75]. Studies in the literature indicate that for improving the customer experiences, environmentally friendly last-mile delivery is an important factor which increases the importance of last-mile delivery's sustainability aspect [76]. However, when focused on the adoption of electric vehicles, such as electric vans, the sector experts present reservations for not fully converting to electric vehicles [77]. Without any incentives, concerns of range, cargo weight, insufficient charging stations, and delays due to charging, are the biggest barriers of why electric vehicles are not being fully adopted. The range of electric vehicles can vary due to factors such as traffic, weather, and weight [78]. Studies that can help the planners to predict the range of electric vehicles are available in the literature. In a study, a ML based model is trained for predicting the range of the given electric vehicle which can perform with an error less than 10% [79].

A significant amount of work is being conducted in this field. New, environmentally friendly technologies, such as electric vehicles with their zero-emission capabilities

have a significant potential. However, it is important to consider the economic aspect as well since the implementation of this technology require a significant initial investment. Therefore, the proposed solutions must also be evaluated in terms applicability and cost effectiveness.

4. METHODOLOGY

In this section, the proposed agricultural logistics method, the simulation environment, test scenarios and the results of the case study are presented. The flowchart of this section is presented in the figure below (Figure 4.1).

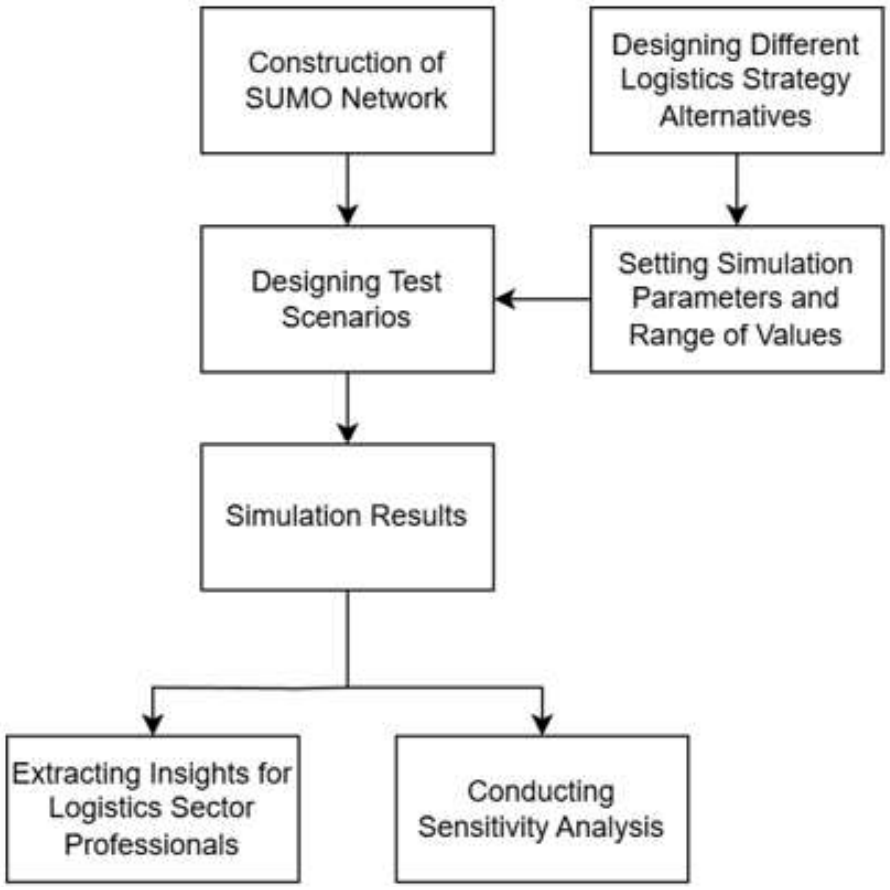

Figure 4.1. Flowchart of the proposed model's methodology.

4.1. Proposed Model

Countries throughout the globe are taking action towards constructing safe and robust supply chains, especially for essential sectors such as agricultural logistics. Emerging risks such as the latest geopolitical instabilities and increasing effect of climate change, have amplified this urgency [80]. In addition to economic costs, the envi-

ronmental costs need to be considered while developing new or improving the existing supply chain infrastructures. Logistics sector professionals and policymakers are all working on innovative approaches and systems for improving their supply chain operations. Additionally, new methodologies and concepts on this topic are being proposed in different studies in the literature [81, 82]. However, there is a lack of collaborative research that propose practical, efficient, sustainable and eco-friendly systems that can actually be implemented by logistics experts that specializes in agricultural logistics and policymakers. In the majority of these studies, the economic feasibility of the proposed system is overlooked within specific country contexts. Even though significant economic and environmental benefits can be obtained, these solutions are rarely considered as practically applicable by professionals. Therefore, there is a gap in the literature of solutions that explicitly consider practical applicability, especially within the agricultural logistics field of developing countries. This is especially important for the benefit of both producers and consumers.

The field of transportation is one of the largest GHG emission contributors [83]. In the US transportation section has overtaken the power sector in terms of GHG emission levels [84]. These emission levels are also strongly influenced by the types of vehicles used. In developing countries such as India and Pakistan, road transportation has the largest share of logistics operations [85, 86]. The main difference between developed and developing countries is that the vehicle types that dominate these transportation operations are vehicles that are inefficient and environmentally unsustainable, such as diesel fuel trucks. In order to decrease the emission levels, alternative zero-emission energy resources, such as electrification of transportation, is essential [87]. However, the required energy to operate these electrified vehicles must be generated by renewable energy sources so that the potential environmental benefits can be maximized [88]. While developed countries can allocate their resources for electrifying their entire logistics fleet, this is much more difficult for developing countries with limited budgets [89]. Therefore, for developing countries, prioritizing the utilization of existing infrastructure with minimal immediate development is much more practical, such as railroad systems with their established networks.

According to the European Commission, shifting the freight traffic towards sustainable modes, such as railroad transport, is essential for decreasing the overall GHG emission levels of the transportation sector [90]. United States Environmental Protection Agency has reported that in 2022, share of GHG emission is 2% for railroad systems. [91]. For road transportation (e.g., light, medium and heavy-duty trucks) this value increases up to 80% which is much more significant. It is much more efficient to utilize the railroad systems for long-haul transportation and make use of road transport for the first and last-mile delivery operations for the food supply-chain [92]. By increasing the share of rail transportation, significant benefits in terms of decreased emission levels and lower average transport costs per ton mile [93]. However, it is also important to optimize the management of cargo transfer between road-rail systems for minimizing the delays that can cause significant losses due to the perishability of food products during their transportation [94]. It is also important to not generate unnecessary trips that can reduce the benefits of this modal-shift (e.g., decreased traffic loads, road maintenance costs). For instance, the train stations and logistics centers can be utilized as a food-marketplaces where buyers and sellers can conduct their businesses here. As a result, the need for transporting food products within the city can be eliminated. In summary, in addition to shifting towards more efficient and sustainable transportation modes, smart management methodologies and effective use of the available infrastructure is a must for optimizing the agricultural logistics operations. In many developing countries, the majority of food transportation relies on road transportation with diesel fuel trucks [85, 86]. As an example, a sketch for the current state of agricultural logistics flow in TC is presented in Figure 4.2. Road transportation is the dominant mode for transporting the food products from producers to consumers. After the buyer purchases the food products from the farmer, a truck driver is hired for delivering these goods to another location, such as a food-marketplace in a city. This driver then delivers the cargo to the buyer's representative in the food marketplace and a price for the agricultural products is determined based on the accumulated costs. Afterwards, the supermarket-buyers purchase the desired products for selling in their stores or storing it in their warehouses. This last-mile trip is also done with trucks.

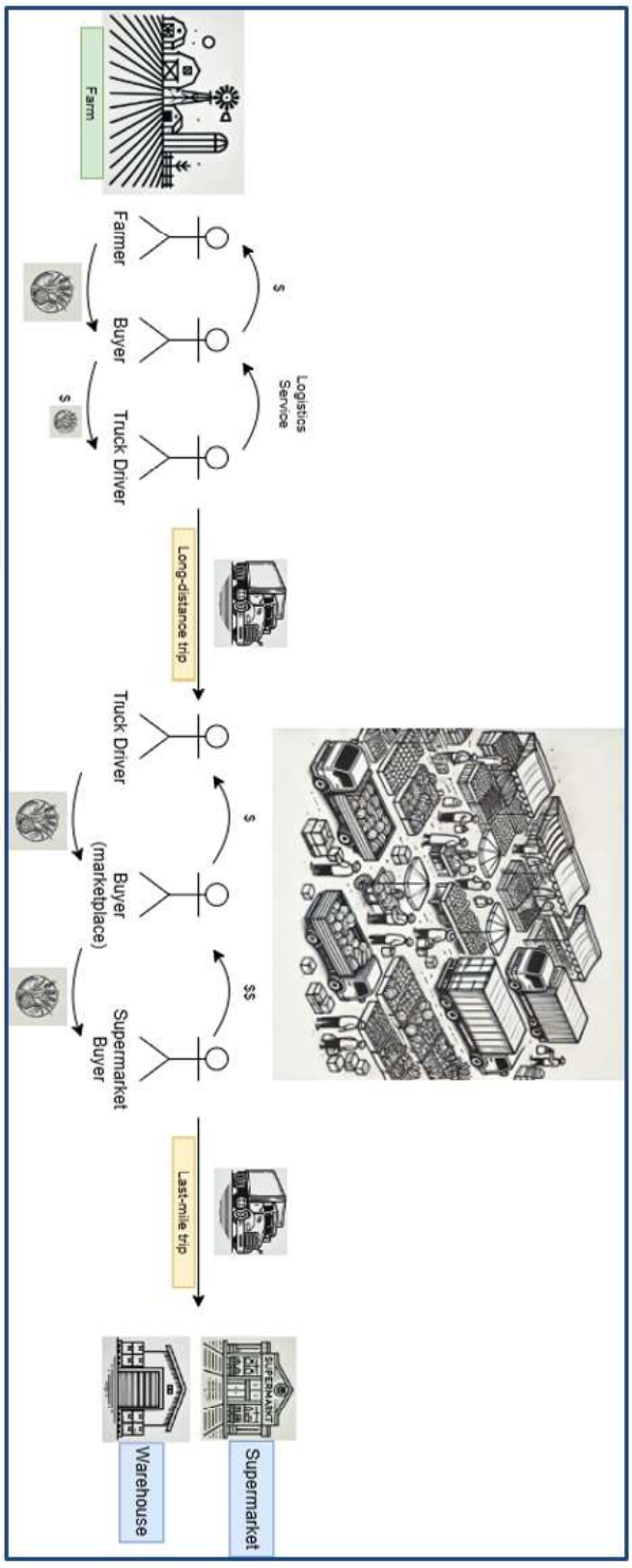

Figure 4.2. Traditional food logistics system sketch.

Road transportation has advantages such as flexible planning, quick delivery, and being able to access remote areas [95]. However, these benefits are outweighed when these vehicles need to travel long distances. Economic and environmental costs become greater than the mentioned advantages when the travel distance of these vehicles increases. Furthermore, as the number of traveling trucks on the freeways and highways increase, road maintenance costs increase and more traffic for other vehicles on the same route is contributed.

The intermediaries in the food marketplaces are another factor that causes these price hikes. In developing countries tracking the products that arrive to these marketplaces is challenging. Due to this lack of transparency, the brokers have the opportunity to set prices in an inconsistent manner. For example, in TC it is estimated that 50% of the transported food products are not being properly tracked [96]. This situation causes drastic daily price fluctuations which causes further unpredictability of food prices. Therefore, in addition to utilizing efficient and sustainable transportation modes, establishing of smarter and better-tracked hubs, such as train stations, is essential.

The proposed logistics system in this dissertation aims to decrease the price hike during the farm-to-fork journey by prioritizing efficient, eco-friendly and sustainable transportation modes (Figure 4.3). The main idea is to maximize the utilization of railroad transportation and minimize the number of trips to deliver the food product to its final destination (e.g., market, warehouse). In order to reduce the number of trips and maximize the utilization of available transportation facilities, the train stations that the freight train is planned to arrive is going to be used as a food marketplace (Figure 1.1). This will also increase the level of trackability of the food cargo. Because trains are traveling in a much more planned manner (e.g., schedules) tracking its cargo and the set prices will be much easier to track [97]. By using the train station as a food marketplace, the need for additional trip between the train station and another marketplace will be eliminated. This may also decrease the traffic load in the local roads due to decreased number of trucks on the roads, both in local roads and freeways.

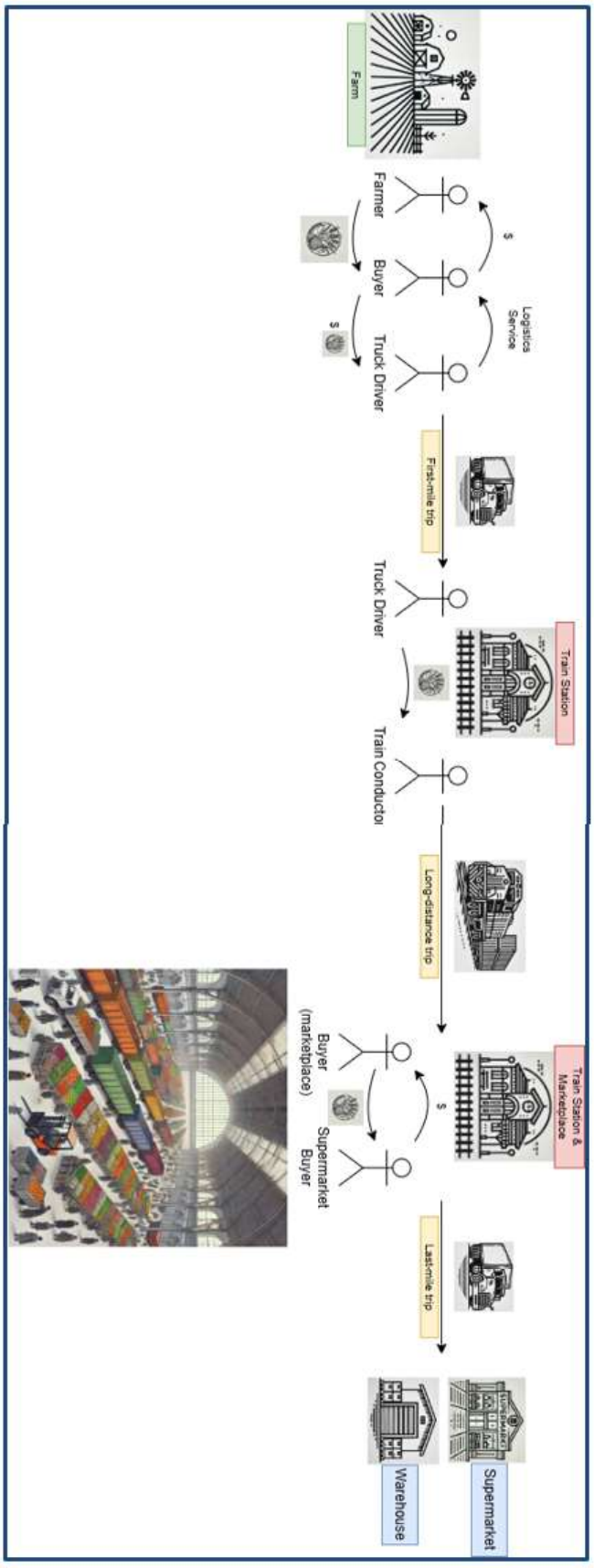

Figure 4.3. Proposed food logistics system sketch.

The supermarket buyers can purchase their products from the intermediaries that are in the train station marketplaces or they can collect their cargo that has been pre-purchased directly from the producer. Increasing the share of railroad transportation for logistics operations can also help reducing the impact of potential future emission taxes for imports and exports. This is especially important for countries that have high volume of trade with EU countries, such as TC. By decreasing the emission levels due to logistics operations, the total financial load due to emission taxes can be reduced.

4.2. Case Study

A semi-synthetic simulation network is constructed to test proposed model using a microscopic traffic simulation tool. The proposed model is evaluated under different conditions. Its results are compared with the alternative logistics strategies. In this dissertation, SUMO (version 1.22.0) is used as the simulation environment [14]. SUMO is an open-source traffic simulation package. It provides the option for flexible scenario creation. Using TraCI (version 1.22.0) and Libsumo (version 1.22.0), it allows access to a running traffic simulation for changing the behavior of the vehicles in the simulation and collecting values from the simulation and specific vehicles. The simulation code is written in Python syntax (version 3.13.2). The simulation code is available in a private GitHub repository [98].

4.2.1. Alternative Logistics Strategies

A total of 6 alternatives are evaluated. Alternative A1 is selected as the base alternative, in which the entire cargo between OD is transported with diesel fuel trucks only. In Alternative A2, which is a variation of the base alternative, only electric trucks are utilized for carrying all of the cargo.

Variations of the proposed model, in which different fuel-type vehicles are utilized, are tested in alternatives A3, A4, A5, and A6. The first and last-mile trips of the logistics are done with trucks (e.g., diesel or electric trucks) and the long-haul

transfer is done with freight trains (e.g., diesel or electric freight trains). The trucks will depart from the origin and deliver their cargo to the train station where they will load their cargo to freight trains. The fully loaded freight train, according to its given cargo capacity, will travel to its final destination and unload its content there to the trucks that are waiting to be loaded. Finally, these trucks will deliver the cargo to its final location. In Table 4.1, summarized information about the tested alternatives is presented. Details about this process and how they are implemented in the simulation are explained in detail in the following sections.

Table 4.1. Alternative logistics strategies to be tested in SUMO environment.

Alternative ID	**Type**	**Long Distance Vehicle Type**	**Short Distance Vehicle Type (First/Last Mile Trips)**
A1	Baseline	Diesel truck	-
A2	Baseline variation	Electric truck	-
A3	Proposed model variation	Diesel freight train	Diesel truck
A4	Proposed model variation	Diesel freight train	Electric truck
A5	Proposed model variation	Electric freight train	Diesel truck
A6	Proposed model variation	Electric freight train	Electric truck

4.2.2. SUMO Network Details

The SUMO network includes two main files: network geometry file and the vehicle and flow properties file. By combining these two, a SUMO configuration file is generated. A network for evaluating the alternative strategies has been designed in the SUMO environment (Figure 4.4). The network consists of local roads, a freeway, and a railroad network:

(i) The local roads represent the roads in urban or relatively populated areas where the traffic is more congested, roads are more constraining, and speed limits are low. By changing the lengths of these roads, potential benefit of placing farms and warehouses closer to train stations and freeway networks is investigated.

(ii) The freeway represents the intercity roads where speed limits are high and road geometry is much more liberating. In the baseline alternatives (A1 and A2) the trucks travel on this road section. The length of freeway and the maximum speed of trucks are changed for each tested scenario for observing the influence on the performance of baseline alternatives.

(iii) The railroad represents the connection between two cities. Similar to freeway, the length of this section is changed in order to observe the potential of the proposed model for different types of vehicles.

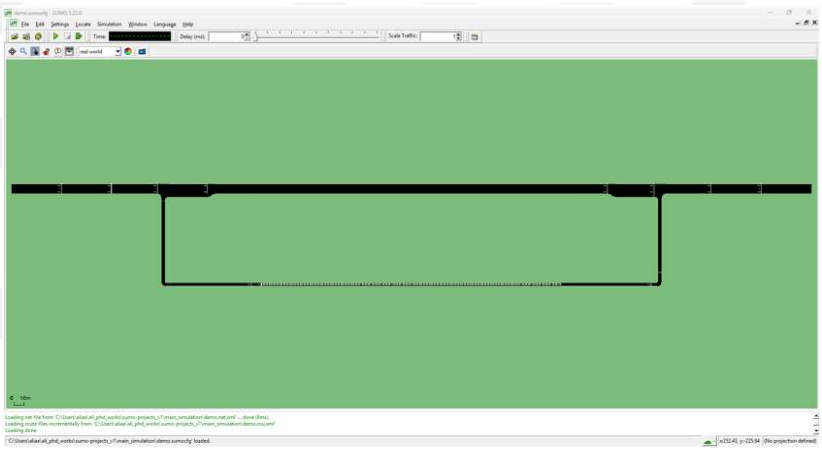

Figure 4.4. The SUMO network.

Trip origin (e.g., farm, warehouse) and destination (e.g., supermarket, warehouse) are located at the bottom left and bottom right corners of the constructed network, respectively. The upper section of the network contains a freeway where vehicles are constantly being inserted until the simulation ends. The railroad that connects the long distance between OD through train stations, is available in the bottom section of the network. In order to provide a more detailed view of the simulation network, the left and right parts of the network are presented separately in Figure 4.5 and Figure 4.6, respectively.

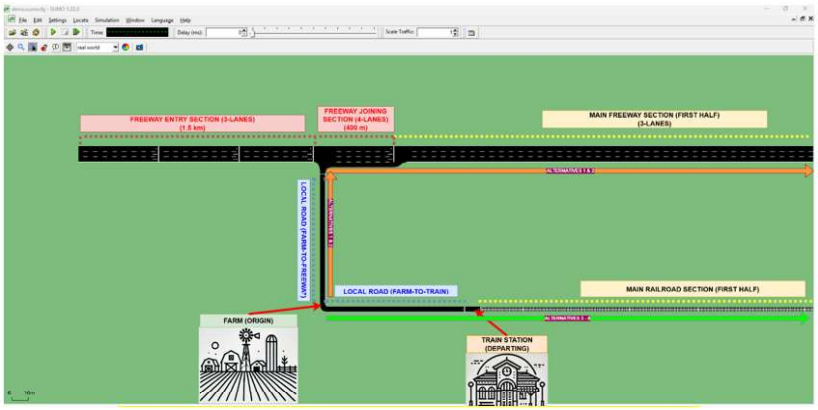

Figure 4.5. Detailed view of the left-half of the simulation network.

All the local roads have single lane. The maximum allowed speed on these roads is assumed as a constant value of 50 km/hr. The lengths of these local roads vary according to the scenario being tested. These roads are providing connections between the farm and the freeway, the freeway and the supermarket/warehouse, the farm and the departing train station, and the arrival train station and the supermarket/warehouse.

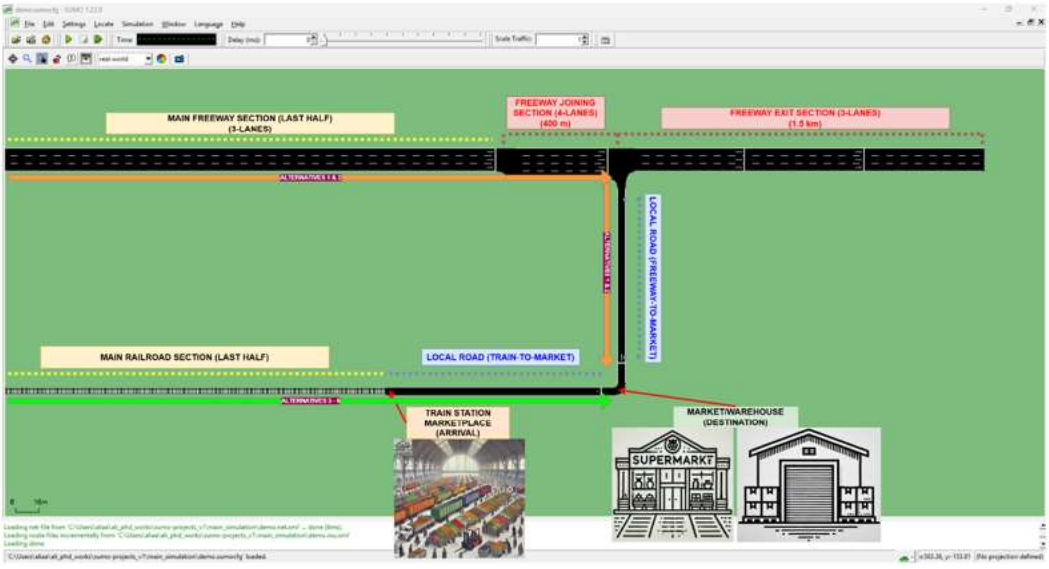

Figure 4.6. Detailed view of the right-half of the simulation network.

The freeway section consists of a 3-lane road with maximum allowed speed of 140 km/hr [105]. At intersections with local roads, the number of lanes increases to 4 lanes

for a length of 400 meters. At points where local roads connect to the freeway, the road section widens to four lanes for 400 meters. On this this freeway a mixed traffic flow, composed of passenger cars and trucks, is generated using a Poisson distribution. As these freeways are assumed to connect a rural area and a populated area, rates of 0.05 and 0.02 are selected for passenger cars and trucks, respectively, for this flow [99, 100]. The properties of these vehicles in the mixed traffic flow are presented in the table below (Table 4.2). In order to avoid increasing the complexity of the simulation, SUMO's default values for these vehicle types are used.

Table 4.2. Descriptives statistics of participants.

Vehicle Parameter	**Passenger Car Value**	**Truck Value**
Maximum acceleration	2.6 m/s^2	1.3 m/s^2
Maximum deceleration	4.5 m/s^2	4.0 m/s^2
Length/Width/Height	5 m / 1.8 m / 1.5 m	7.1 m / 2.4 m / 2.4 m
Mass	1500 kg	12000 kg
Maximum speed	140 km/hr	80 km/hr
Minimum gap	2.5 m	2.5 m
Sigma	0.9	0.9

The railroad network contains a single railway that connects the two train stations. These stations are located near the farm and the supermarket. The maximum allowed speed on this track is also assumed as 140 km/hr. The freight trains depart based on the frequency that is predetermined according to the tested scenario (e.g., every 30 minutes, 2 hours, etc.). The length of this railroad varies between 200 km and 700 km.

In alternative A1 (baseline alternative) diesel fuel trucks travel from the origin (e.g., farm, warehouse) to the destination (e.g., supermarket, warehouse). This journey is made only through the freeway network, where a mixed traffic flow is present. Electric trucks in alternative A2 (baseline alternative variation) also follow the same route.

In alternatives A3, A4, A5, and A6 (variations of proposed model), the trucks

travel from the origin to the nearest train station via local roads. These trucks transfer their cargo to freight trains. These trains handle the long-haul portion of the logistics operation. At the end of the railroad trip, the cargo is unloaded onto the trucks for the last-mile trip.

The simulation loop stops when the entire cargo has been transported from the origin to the final destination. This condition is set as the stopping criteria for the simulation.

4.2.3. Assumptions

In this simulation, the following assumptions are made in order to improve the simulation's real-life similarity and its run-time performance of the simulation. Insights obtained from the interviews with experts are utilized for determining some of the assumptions [101]. These assumptions are as follows:

(i) The perishability of the transported products has been disregarded. The main focus is on durable agricultural products, such as potatoes, onions, and wheat. Discussions with logistics experts indicate that these lower-value, high-demand products present significant efficiency challenges. The cost of transportation for a given amount of goods is relatively similar, regardless of their value. Therefore, for low-value products, transportation costs constitute a much higher share of the total cost, which is the root cause of efficiency challenges of these types of goods. For example, transportation cost for potatoes is approximately 30% of their total cost, whereas for a higher-value product, such as strawberries, this value is significantly lower, around 10%.

(ii) To maintain the focus on developing countries, in this dissertation only trucks are considered for road transportation operations [102]. Other vehicle types, such as trailers, are excluded.

(iii) Scope of this simulation covers the period from the point that the fully loaded trucks depart from the origin (e.g. farm or warehouse) to the point at which all

cargo has arrived at the final destination (e.g. supermarket or warehouse).

(iv) Trucks are assumed to travel in a fleet-like manner. Every 60 seconds, the trucks depart from origin.

(v) To simplify the simulation, electric vehicles are assumed to have infinite battery capacity. Charging stops are not simulated. Instead, it will be assesed through a sensitivity analysis based on different levels of battery capacity and charging speeds.

(vi) The simulation represents cargo transportation and its mass by changing the mass properties of the trucks and trains.

(vii) According to interviews with logistics experts and regulations from the General Directorate of Highways, total weight of trucks and its cargo cannot exceed 26 tons. Therefore, this value is utilized for restricting the payload of each truck. Furthermore, the reduced cargo capacity of electric trucks is accounted for to represent their greater empty weight compared to diesel trucks. These vehicle-specific parameters are detailed in Section 4.2.4.2.

(viii) Empty weight difference between diesel and electric freight trains are ignored. The cargo capacity of a freight train is set according to the specific scenario that is being tested.

(ix) In SUMO, the default car-following model is the Krauss model and it is selected as the car-following model for all road transportation vehicles in this simulation (e.g. trucks, passenger cars) [103, 104]. A key parameter of this model is called α which represents the drivers' level of imperfection. It has a default value of 0.5. This value converges towards 0 for a perfect driver and 1 for highly imperfect drivers. It can also be assumed that this value increases as the drivers' level of unfamiliarity with the road that they are traveling and their urgency to arrive at their destination. Given that majority of road segments in this simulation network are assumed as intercity roads, selecting a sigma value close to 1 is reasonable. As a result, a sigma value of 0.9 is set for all road transport vehicles.

(x) A free-flow traffic state is assumed for the freeway section of the simulation network. This is based on the assumption that this freeway section is connecting a rural area and a populated area with relatively light traffic conditions. Therefore,

utilizing Poisson distribution for modeling the traffic flow is justified [99, 100]. A flow rate of 0.05 which is the default value in SUMO, is selected for modeling passenger car traffic flow. To create a mixed-traffic flow, trucks are introduced at a flow rate of 0.02 with their presence limited to a maximum of 50% of the total freeway traffic. These flow rates are constant for the entirety of the simulation.

(xi) It is assumed that the simulation network is located in TC. The maximum speed limits for all local road segments, the freeway section are selected as 50 km/hr and 140 km/hr, respectively [105]. For the freight trains the speed limit is assumed as 50 km/hr, which can be considered as the mean value of speed limits of different studies [106].

(xii) The lengths of main roads (e.g., freeway and railway) range from 200 km to 700 km, increasing by 100 km at each step.

(xiii) The local roads of the simulation network all have single lane. No traffic flow is generated on these roads. Instead, the traffic congestion is simulated through causing the vehicles to change their traveling speed values more frequently [107]. This is achieved through setting the driver imperfection level of the car-following model (α) close to 1.

(xiv) For Alternatives 1 (baseline – diesel trucks) and 2 (baseline variation – electric trucks), truck speeds are determined by sampling from a normal distribution [100]. The mean of the distribution is selected as the maximum allowed speed on the freeway in the given scenario. The standard deviation is set as 10% of the given limit.

(xv) For Alternatives 3, 4, 5, and 6 (proposed model's alternatives) truck speeds on the local roads are assigned by randomly sampling from a normal distribution [100]. The mean of this distribution is set as 50 km/hr (the local roads' speed limit) and a standard deviation of 10% of this mean value (e.g. 5 km/hr). The same approach is used for determining the speed of freight trains, with the mean of the normal distribution set to railroad section's maximum speed limit and 10% of that limit [108].

(xvi) According to interviews with logistics experts, the mean duration of loading or unloading a truck is approximately 45 minutes. To introduce a degree of variability,

these durations are set by selecting a random sample from a normal distribution with a mean of 45 minutes and standard deviation of and 5 minutes for each vehicle [101].

(xvii) In the proposed model, trucks that have arrived at the train station after their first-mile trip, begin loading their cargo onto the freight train without any delay. To reflect labor and spatial limitations at some level, the number of trucks that can simultaneously load their cargo onto the train is set as 10. Trucks that are waiting proceed in a first-come, first-served manner, occupying the first available loading slot [101].

(xviii) In SUMO different emission classes are defined for various vehicle types. These emission classes are used to model the fuel consumption and emission levels. For electric trains and diesel trains, the default emission classes are named "Zero" and the dirtiest diesel emission of HBEFA3/HDV_D_EU0 model (diesel driven heavy duty vehicle Euro-0 norm), respectively [111]. However, these classes are not suitable for properly representing fuel consumptions of these vehicle types. Using "zero" as the emission class does not provide any fuel consumption output which literally makes the electric freight train a zero-emission vehicle. As for the diesel freight train's default emission class, because it is designed mostly for road vehicles, it severely underestimates the fuel consumption of this vehicle type. To address these limitations, "Energy" emission class is assigned to both types of train which presents the fuel consumption in Wh. For diesel freight trains, the obtained value is converted to diesel fuel consumption by adjusting electric and diesel motors' efficiency levels. This approach allows for obtaining more realistic energy consumption estimates and prevents underestimating the fuel consumption. The detailed explanation of how these conversions are made are presented in Section 4.4.1.

(xix) At the end of the first-mile trip, trucks will load their cargo into FEUs on wagons. The freight train's locomotive will then attach to these wagons and then depart at its scheduled departure time. The locomotive will only carry the amount of cargo according to its given capacity. Both the train's cargo capacity and its scheduled departure time are defined by the simulation scenario's parameters.

(xx) The freight train's wagons are modeled after a 4-axled flat open wagon [109]. According to the International Union of Railways, utilization of this type of container and wagon combination for carrying durable food products is standard practice due to efficiency and safety concerns [110]. Hence, these wagons can carry up to 2 FEUs.

(xxi) Upon the freight train's arrival at its destination, it is assumed that the trucks are available to unload cargo from the wagons. Therefore, delays caused by truck unavailability and train idle waiting times are disregarded. Similar to the loading process, it is assumed that a maximum of 10 trucks can unload the cargo simultaneously. Trucks depart as soon as they are fully loaded. If the departure time difference of two trucks is less than 60 seconds, the subsequent truck's departure time is delayed by 60 seconds [101].

4.2.4. Simulation Parameters and Scenarios

In this section the simulation parameters are presented in a detailed manner. The parameters are grouped into three categories; network parameters, vehicle parameters and logistics operation scenario parameters. Further explanations are provided in their respective subsections.

4.2.4.1. Network Parameters. The simulation network features several key spatial parameters (Table 4.3). 3 different types of road sections are available in the network: freeway, local roads (farm-freeway, freeway-supermarket, farm-train station, train station-supermarket), and railway. On freeway and railway sections the long-haul portion of the logistics operations is conducted. The tested values of the long-haul distance start from 200 km up to 700 km, with increments of 100 km. For local roads, the speed limit is set as 50 km/hr for all segments. It should also be noted that the tested lengths of the local roads are applied for all local road sections.

Table 4.3. Network parameters.

Parameter Name	**Value Range**	**Unit of Measurement**
Freeway length	200 – 300 – 400 – 500 – 600 – 700	km
Freeway speed limit	140	km/hr
Railway length	200 – 300 – 400 – 500 – 600 – 700	km
Railway speed limit	50	km/hr
Local roads' length	20 – 40	km
Local roads' speed limit	50	km/hr

4.2.4.2. Vehicle Parameters. In this section, detailed information for modeling the logistics vehicles (e.g., diesel trucks, electric trucks, diesel freight trains, electric freight trains) are presented. These values are obtained through a literature review and interviews with logistics experts. Descriptions of the parameters and the reference for its set value is presented in each vehicle type's respective table.

For modeling the diesel trucks, the default parameters provided by SUMO is utilized [111]. As mentioned in the section 4.2.3, the sigma value of the car-following model is set as 0.9. Additionally, the maximum allowed speed of these vehicles depends on the road that they are traveling and the given scenario. On local roads, these trucks travel with a speed of approximately 50 km/hr, assuming that they are driving in a built-up area. On freeways, the trucks are tested under two different speed limits: 50 km/hr and 80 km/hr. According to the logistics experts, trucks drivers have a tendency to travel with low speeds due to fuel consumption concerns [101]. Therefore, these two values are selected to evaluate the difference between a fuel conservative driver and non-fuel-conservative driver. Detailed information is provided in Table 4.4.

Table 4.4. Vehicle parameters of diesel trucks.

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
vClass	Vehicle class	-	truck	[111]
length	Vehicle length	m	7.1	[111]
width	Vehicle width	m	2.4	[111]
height	Vehicle height	m	2.4	[111]
mass	Vehicle mass	kg	12	[111]
minGap	Minimum headway distance	m	2.5	[111]
accel	Maximum acceleration	m^2/s	1.3	[111]
decel	Maximum deceleration	m^2/s	4.0	[111]
maxSpeed	Maximum allowed speed	km/hr	50 (on local roads) 50/80 (on freeway, based on given scenario)	[101]

While modeling the electric trucks some parameters are taken as the same value as the default diesel fuel truck (e.g., vClass, length, width, height, minGap, accel, decel, maxSpeed). However, there are some key differences. The first being is the mass of the electric truck. Because of the battery, the vehicle mass increases significantly according to other studies that model electric trucks, which causes a decrease of its cargo capacity [112]. Additionally, in order to model an electric vehicle SUMO requires many other parameters to be set. These parameters with their descriptions are presented in Table 4.5.

Table 4.5. Vehicle parameters of electric trucks.

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
vClass	Vehicle class	-	truck	[111]
length	Vehicle length	m	7.1	[111]

Table 4.5 Vehicle parameters of electric trucks. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
width	Vehicle width	m	2.4	[111]
height	Vehicle height	m	2.4	[111]
mass	Vehicle mass	kg	16	[112]
minGap	Minimum headway distance	m	2.5	[111]
accel	Maximum acceleration	m2/s	1.3	[111]
decel	Maximum deceleration	m2/s	4.0	[111]
maxSpeed	Maximum allowed speed	km/hr	50 (on local roads) 50/80 (on freeway, based on given scenario)	[101]
Has.battery. device	Must be set as true for electric vehicle modeling	bool	true	[113]
airDrag Coefficient	Air drag coefficient	-	0.63	[112]
device.battery. capacity	Maximum Battery capacity	Wh	825	[112]
frontSurfaceArea	Front surface area of vehicle	m2	6.25	[111]

Table 4.5 Vehicle parameters of electric trucks. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
maximumPower	Maximum power which the vehicle can achieve	W	188	[112]
rollDrag Coefficient	Rolling resistance coefficient	-	0.007	[112]
rotatingMass	Total mass of internal rotating elements (calculated as approximately 1.5% of vehicle mass)	kg	250	[113]
Propulsion Efficiency	Drive efficiency of electric vehicle	-	0.9	[113]
Constant PowerIntake	Power that is constantly being consumed by electronic parts of the vehicle	W	100	[113]

Table 4.5 Vehicle parameters of electric trucks. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
device.battery. maximum ChargeRate	Maximum charging rate of the battery	W	150	[113]
Recuperation Efficiency	Recuperation efficiency due to breaking	-	0.9	[113]
Stopping Threshold	Maximum speed for charging to start	m/s	0.1	[113]

In SUMO there are default train models available that comes with the tool. Modeling a freight train is not one of the train classes available by default. The documentation for modeling custom trains is very limited. Therefore, in order to model custom and electric freight trains the same approach for modeling the electric trucks is employed with some differences.

The diesel freight train is modeled after EMD SD70ACe because of its widespread use and the available detailed information [114]. This model has been introduced in 2005. It is still being widely used across North America for heavy-haul freight logistics operations. As mentioned in Section 4.2.3, the available emission classes in SUMO underestimates the diesel fuel consumption of freight trains significantly. Therefore, using this train model's parameters, an electric freight train is modeled by setting the emission class as "Energy" to collect the fuel consumption in Wh. This electric consumption is then converted to diesel consumption. Details regarding this conversion is presented in Section 4.4.1. Similar to the modeling of electric trucks, additional parameters are also needed to be set for modeling this train. The descriptions and values of these parameters are presented in Table 4.6.

Table 4.6. Diesel freight train parameters.

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
vClass	Vehicle class	-	rail	[111]
emissionClass	Emission class for determining the type of fuel consumption	-	Energy	[113]
length	Vehicle length (locomotive and carry wagons)	m	22.63 + (length of container wagons)	[114]
width	Vehicle width	m	3.2	[114]
height	Vehicle height	m	4.9	[114]

Table 4.6 Diesel freight train parameters. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
mass	Vehicle mass	kg	185,000 + (mass of container wagons)	[114]
maxSpeed	Maximum allowed speed	km/hr	50	[101]
airDrag Coefficient	Air drag coefficient	-	1.1	[115]
frontSurface Area	Front surface area of vehicle	m2	15.7	[114]
Maximum Power	Maximum power which the vehicle can achieve	W	3,162,644.625	[114]
rollDrag Coefficient	Rolling resistance coefficient	-	0.004	[115]
Rotating Mass	Total mass of internal rotating elements (calculated as approximately 6% of vehicle mass)	kg	11,1	[116]

Table 4.6 Diesel freight train parameters. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
Propulsion Efficiency	Drive efficiency of electric vehicle	-	0.9	[113]
Constant PowerIntake	Power that is Constantly being consumed by electronic parts of the vehicle	W	100	[113]
device. battery. Maximum ChargeRate	Maximum charging rate of the battery	W	150	[113]
recuperationEfficiency	Recuperation efficiency due to breaking	-	0.9	[113]
Stopping Threshold	Maximum speed for charging to start	m/s	0.1	[113]

For modeling the electric freight train, the FLXdrive heavy-haul battery-electric freight train is used as the reference model [117]. This is a locomotive that has the goal of replacing diesel locomotives in the near future. It is also considered as the world's first 100% battery-electric heavy-haul locomotive. Using information from the datasheet and the default properties of Rail vehicle class, the selected parameters for modeling an electric freight train is presented in Table 4.6.

Table 4.7. Electric freight train parameters.

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
vClass	Vehicle class	-	Rail	[111]
length	Vehicle length	m	22.7 + (length of container wagons)	[117]
width	Vehicle width	m	4.4	[117]
height	Vehicle height	m	3.0	[117]
mass	Vehicle mass	kg	209,000 + (mass of Container wagons)	[117]
minGap	Minimum headway distance	m	5	[111]
accel	Maximum acceleration	m2/s	0.25	[111]
decel	Maximum deceleration	m2/s	1.3	[111]
maxSpeed	Maximum allowed speed	km/hr	50	[108]
Has.battery. device	Must be set as true for electric vehicle modeling	bool	true	[113]
airDrag Coefficient	Air drag coefficient	-	1.1	[115]

Table 4.7 Electric freight train parameters. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
device. battery. capacity	Maximum battery capacity	Wh	7,000,000	[117]
frontSurface Area	Front surface area of vehicle	m2	13.2	[117]
Maximum Power	Maximum power which the vehicle can achieve	W	3,200,000	[117]
rollDrag Coefficient	Rolling resistance coefficient	-	0.004	[115]
Rotating Mass	Total mass of internal rotating elements (calculated as approximately 6% of vehicle mass)	kg	12,506	[116]
Propulsion Efficiency	Drive efficiency of electric vehicle	-	0.9	[113]
Constant PowerIntake	Power that is constantly being consumed by electronic parts of the vehicle	W	100	[113]

Table 4.7 Electric freight train parameters. (cont.)

Name	**Description**	**Unit of Measure**	**Value/s**	**Value Reference**
device.battery. maximum ChargeRate	Maximum charging rate of the battery	W	150	[113]
Recuperation Efficiency	Recuperation efficiency due to breaking	-	0.9	[113]
Stopping Threshold	Maximum speed for charging to start	m/s	0.1	[113]

To reduce the complexity of the simulation, parameters, such as constantPowerIntake, device.battery.maximumChargeRate, recuperationEfficiency, and stoppingThreshold, are set as the same default SUMO value for all electric vehicles. These parameters are more important for the charging aspect of electric vehicles. However, as mentioned in Section 4.2.3, the charging aspect is neglected. Instead, the potential delays due to charging processes are assessed through a sensitivity analysis.

These freight trains are responsible for the long-haul portion of the logistics operation. At the end of the first-mile trip, the trucks will load the cargo into the containers that are loaded on 4-axled flat wagons [109]. When the loaded amount is equal to the cargo capacity of the freight train and the departure time of the freight train has arrived, the locomotive of the freight train will attach itself to the loaded wagons and then depart from the train station. According to the number of containers and wagons, the length and mass of the freight train in the simulation is adjusted. For safety concerns it is recommended that a maximum of 2 FEUs is allowed for transportation on a 4-axled flat wagon. Detailed container and wagon information about the important parameters for the simulation are presented in Table 4.7 [118].

Table 4.8. FEU and 4-axled flat wagon parameters.

Parameter Name	**Unit of Measure**	**Value**
Wagon length	m	27
Wagon tare mass	kg	25000
FEU tare mass	kg	3480
FEU cargo capacity	Kg	27000
Number of FEU allowed per wagon	-	2

4.2.4.3. Logistics Operation Parameters. The scope of this dissertation covers the scenarios that are presented in Table 4.8. In total 792 different scenarios are tested. 144 of these scenarios are covering the alternatives of baseline variations. The remaining 648 scenarios are specifically designed for the proposed model's variations.

Table 4.9. Tested parameters for different scenarios.

Parameter Name	**Tested Values**	**Unit of Measurement**	**Tested for Alternatives**
Cargo mass	500 – 600 – ... – 900 – 1000	tons	A1, A2, A3, A4, A5, A6
Truck departing frequency	60	s	A1, A2, A3, A4, A5, A6
Local roads' length	20 – 40	km	A1, A2, A3, A4, A5, A6
Local roads' speed limit	50	km/hr	A1, A2, A3, A4, A5, A6

Table 4.9 Tested parameters for different scenarios. (cont.)

Parameter Name	**Tested Values**	**Unit of Measurement**	**Tested for Alternatives**
Truck cargo capacity	14 (for diesel fuel trucks) 10 (for electric trucks)	tons	A1, A2, A3, A4, A5, A6
Freeway length	200 – 300 - . . . - 700	km	A1, A2
Max. Allowed speed of trucks on freeway	50 – 80	km/hr	A1, A2
Railroad length	200 – 300 – . . . – 700	km	A3, A4, A5, A6
Railroad speed	50	km/hr	A3, A4, A5, A6
Mean of cargo loading/unloading duration for trucks	45	minutes	A3, A4, A5, A6
Standard deviation of cargo loading /unloading duration for trucks	5	minutes	A3, A4, A5, A6
Max. number of loading/ unloading truck slots	10	slots	A3, A4, A5, A6
Freight train departing frequency	0.5 – 2 – 4	hr	A3, A4, A5, A6
Freight train cargo capacity	250 – 500 – 1000	tons	A3, A4, A5, A6

Cargo mass, local roads' length, and long-haul transportation distance (freeway and railroad lengths) are the main parameters that influence the performance of both baseline and proposed models and their variations. The maximum speed of trucks traveling on the freeway is a parameter that is specifically affecting the performance of baseline alternatives (A1 and A2). Whereas parameters that have an effect on the performance of train operations are specifically influencing the performance of the proposed model and its variations (A3, A4, A5, and A6), such as freight train departing frequency and cargo capacity. Certain parameters are taken as constant values as previously explained in Sections 4.2.2, 4.2.3, and 4.2.4 (e.g., truck departing frequency, local roads' speed limit, railroad speed, cargo loading/unloading duration mean and standard deviation, maximum number of slots for loading/unloading trucks, truck cargo capacity).

4.3. Simulation Algorithm

The simulation code is developed using Python syntax. The code is mainly based on the TraCI package. This package enables controlling and modifying vehicle behavior and data collection during simulation runs. Separate algorithms are developed for the baseline alternatives (A1 and A2) and the proposed model alternatives (A3, A4, A5, and A6).

Before starting the simulation loop, the necessary files (e.g., simulation scenarios, vehicle parameters and road network files) are loaded to the simulation environment. The Excel file that contains the simulation scenarios provide the specific parameters for each test scenario. The vehicle parameters provide the crucial parameters of the vehicles that are presented in Section 4.2.4.2 and traffic flow information that are presented in Section 4.2.2. The road network file contains the SUMO network that the given scenario is tested on. After loading these files, the simulation-wide parameters are set.

4.3.1. Baseline Alternatives' Simulation Algorithm

For baseline alternatives, the logistics operations are conducted with only diesel or electric trucks. Truck departure frequency is set as 60 seconds, the local road speed limits are set as 50 km/hr, and the maximum total truck mass is set as 26 tons. After setting these simulation-wide parameters, each scenario is iterated. The maximum freeway speed of trucks, lengths of local roads and freeways, and total cargo mass are retrieved based on the scenario ID.

For each scenario the specified alternatives are also iterated. For baseline alternatives the truck type (e.g., diesel or electric) is determined according to the alternative ID. A truck's cargo capacity is calculated by subtracting the mass of truck from the maximum allowed total truck mass. The total number of trucks required is calculated by dividing the total cargo mass by the truck's cargo capacity and then rounding up the result to the nearest whole number. The simulation time step, total cargo mass transported, and number of dispatched trucks are initialized to zero. An empty list is initialized for tracking the active trucks in the simulation.

The simulation loop is initiated by establishing a connection using TraCI package. A truck departs from the origin if the current truck count is less than the required number of trucks and a 60 second interval has passed since the last departure. When the truck is inserted to the simulation, it is loaded with the cargo amount based which is the minimum of the truck's cargo capacity and cargo amount at the origin. The loaded amount is then subtracted from the cargo amount at the origin and truck's ID is added to the active trucks list for tracking its journey. The departed truck's maximum freeway speed is set by sampling from a normal distribution based on the scenario's maximum allowed freeway speed for trucks. When a truck arrives at its destination, the total cargo mass transported is increased by truck's loaded cargo amount.

The simulation loop terminates when the total cargo transported is equal to the initial total cargo mass and all tracked trucks in the active trucks list have exited the

simulation. Pseudo code representation for the baseline alternatives is presented in Table 4.9.

Table 4.10. Pseudo code of baseline alternatives.

```
Load the Excel file that contains all scenarios and its parameters
Get vehicle masses from vehicle-parameters file and
create a dictionary for each vehicle type
Set truck depart frequency to 60 seconds, local road
maximum speed to 50 km/h (13.89 m/s), maximum truck
mass (cargo+truck) to 26 tons
For each scenario in scenarios;
        Get the total cargo mass, and the alternativeIDs
          to be tested for given scenario
        Set local road travel lengths based on given scenario
        Get maximum freeway speed for trucks
        For each alternativeID in alternativeIDs
              Get truck type based on alternative ID
              Set truck cargo capacity based on its own
                mass and maximum allowed truck mass
              Start logging for the simulation steps
              Set time step, total cargo mass carried
                by trucks, and truck count to 0
              Set empty active trucks list
              Get number of required trucks by
                dividing cargo mass to maximum allowed total truck mass
              Start simulation with SUMO using TraCI
              While True
                If truck count is less than number
                      of required trucks and time step truck depart frequency is 0
                   Get cargo mass to be loaded on truck
                       as the minimum value between truck
                       cargo capacity and cargo at origin
                    Insert a truck, set its speed to maximum
                      allowed freeway speed by sampling from
                      a normal distribution, change its mass by the cargo loaded on it
                   Add this truck ID to the active trucks list
                    Increase truck count by one
                   Subtract loaded cargo on truck from cargo at origin
                For truck in active trucks list
                    If truck is located at the destination
                      Increase the total cargo mass carried
                         by trucks by the cargo amount of the given truck
                If total cargo mass carried by trucks is
                      equal to total cargo mass and all
                      trucks in the active trucks list have left simulation
                Break simulation loop
                Increase time step by 1
```

4.3.2. Proposed Model Alternative's Simulation Algorithm

In the proposed model, the long-haul portion of the logistics operation is handled with freight trains. Trucks are only used for first and last-mile trips. For increased clarity, the pseudo code is presented in a step-by-step manner. Similar to the baseline algorithm, the proposed model's algorithm begins by loading the required files.

Vehicle mass information for both trucks and freight trains is retrieved from the vehicle parameters file. But the cargo capacity is only calculated for trucks as explained in Section 4.3.1. The same simulation-wide parameters as the baseline are set (e.g., truck departure frequency of 60 seconds and a local road speed limit of 50 km/hr). However, several new parameters are introduced for handling the first/last mile trips, loading/unloading operations at the train stations, and train journeys (Table 4.10).

Table 4.11. Pseudo code of proposed model alternatives – setting the simulation-wide parameters.

```
Get vehicle masses from vehicle-parameters file and create
    a dictionary for each vehicle type
Load the Excel file that contains all scenarios and its parameters
Set truck-depart-frequency to 60 seconds, local-road-maximum-
    speed to 50 km/h (13.89 m/s), maximum-truck-mass (cargo+truck) to 26 tons
Set train-maximum-speed to 50 km/h (13.89 m/s)
Set maximum-loading/unloading-slots as 10, loading/unloading-
    mean-duration as 45 minutes and std-dev-duration
    as 5 minutes (normal distribution parameters)
Set container-tare-mass as 3.48 tons and maximum-allowed-cargo load as 27 tons
Set wagon-tare-mass as 25 tons, wagon-length as 27 meters
    and maximum-allowed-container carry count as 2
```

The maximum speed of freight trains is set as 50 km/hr. A maximum of 10 simultaneous loading/unloading truck slots is set. The duration of these loading/unloading

operations is determined through sampling from a normal distribution with mean and standard deviation values of 45 minutes and 5 minutes, respectively. The tare mass of containers is set as 3.48 tons and the maximum allowed cargo load per container is selected as 27 tons. The length and tare mass of wagons is set as 27 meters and 25 tons, respectively. The maximum number of containers a wagon can carry is set as 2.

After these initial parameters are set, the simulation algorithm starts to iterate through each defined simulation scenario. Similar to the baseline algorithm, the total cargo mass, and local road lengths are set according to given scenario. Additionally, train frequency and cargo capacity, and railroad lengths are retrieved based on the scenario.

Within each scenario, each alternative of the proposed model is processed. Based on the alternative ID, the types of trucks and freight trains are determined. Similar to the baseline algorithm, the cargo capacity of the trucks and the number of required trucks are calculated. In addition, number of required freight trains is calculated by dividing the total cargo mass by the cargo capacity of a single train.

Before starting the main simulation loop, several variables are initialized for tracking the logistics vehicle in the simulation. Empty lists are created for tracking the active first-mile and last-mile trucks, and active freight trains. Dictionaries are used for managing the loading and unloading processes at the train stations. Finally, the simulation time step, total transported cargo mass, cargo at the first and last mile train stations, and the number dispatched trains, first-mile trucks and last-mile trucks are all set to zero. Total cargo at the origin is set as the total cargo mass. Afterwards, the simulation is initiated by establishing a connection with the TraCI package (Table 4.11).

Table 4.12. Pseudo code of the proposed model alternatives – process of setting scenario parameters and initializing variables for tracking logistics vehicles.

```
For each scenario in scenarios;
  Set the total cargo mass, and the alternativeIDs to be tested
      for given scenario
  Set train frequency and cargo capacity for given scenario
  Set local road and railroad lengths based on given scenario
  For each alternativeID in alternativeIDs
    Set truck and train types based on alternative ID
    Get truck cargo capacity based on its own mass and
      maximum allowed total truck mass
    Set cargo mass carried by trucks, train count, first-mile
      truck count, and last-mile truck count to 0
    Set cargo at origin as cargo mass
    Set cargo at first-mile-train-station and last-mile-train-station as 0
    Set active-first-mile trucks, first-mile arrived-trucks,
      active-last-mile trucks, and last-mile arrived-trucks,
      loading finished trucks and unloading finished trucks empty lists
    Set active-trains and arrived-trains empty lists
    Set first-mile loading trucks, first-mile waiting-for-loading
      trucks and last-mile unloading trucks dictionaries for
      loading and unloading process tracking
    Get number of required trucks by dividing cargo mass to
      maximum allowed total truck mass
    Get number of required trains by dividing cargo mass to
      train cargo capacity
    Start logging file for logging the simulation steps
    Start connection with SUMO using TraCI
    Start simulation
```

The main simulation loop of the proposed model begins with the dispatch of trucks from the origin for their first-mile trips to the nearest train station. A first-mile truck is inserted every 60 seconds, while the number of dispatched first-mile trucks is less than the number of required trucks. Number of dispatched first-mile trucks is increased by one for each truck insertion. The cargo amount loaded onto each truck is determined by the minimum value between the truck's cargo capacity and the

remaining cargo amount at the origin. The amount of cargo loaded on to the truck is then subtracted from the cargo remained at the origin. Truck's maximum speed is set by sampling from a normal distribution with the mean equal to the local road's speed limit and standard deviation equal to 10% of the local road's speed limit. To track the journey of this truck, its ID is added to the active first-mile trucks list (Table 4.12).

Table 4.13. Pseudo code of the proposed model alternatives – first-mile truck departure process.

```
While True
  If truck count is less than number of required trucks and time
      step mode truck depart frequency is 0
    Get cargo mass to be loaded on truck as the minimum value between
      truck cargo capacity and cargo at origin
    Insert a truck, set its speed to maximum allowed local speed by
      sampling from a normal distribution, change its mass by
      the cargo loaded on this truck
    Add this truck to the active-first-mile trucks list
    Increase first-mile truck count by one
    Subtract loaded cargo on truck from cargo at origin
```

The simulation constantly monitors the journey of these active first-mile trucks. Once a first-mile truck has arrived at the destination (e.g., train station near the origin) its arrival time step and ID are recorded in a dictionary for the loading management of first-mile arrived trucks. As mentioned in Section 4.2.3, it is assumed that the arrived first-mile truck immediately starts its loading process without any delays, if there are available loading slots at the train station. The loading duration for a truck is determined by sampling from a normal distribution (loading duration mean: 45 minutes, loading duration standard deviation: 5 minutes). The sampled duration is adjusted if the loaded cargo of the given first-mile truck is less than its capacity (e.g., duration is halved if the loaded cargo amount is half of truck's capacity). For the given truck the expected loading-finish time step is calculated by adding the loading duration to the truck's arrival time step. This information is stored in the same dictionary for

the loading management of first-mile trucks. The available slots are decreased by one, until the given truck has finished its loading operation.

If all loading slots are occupied at the moment of a first-mile truck's arrival, then its arrival time step and ID are recorded in a separate dictionary. This dictionary is used for tracking the waiting queue of first-mile trucks for loading their cargo. At each time step, the simulation checks the loading status of the first-mile trucks. If a truck has just finished its loading process (e.g., current time step is greater than the expected loading-finish time step for the given first-mile truck), then the cargo amount at the train station near the origin is increased by the truck's cargo amount and the available slots is increased by 1. If there are any trucks waiting at the train station, the one that has arrived the earliest, instantly moves to a loading slot and starts its loading process. This new truck's loading information is again stored in the dictionary for first-mile loading trucks. This loading operation is repeated until all first-mile trucks have finished their loading processes. The pseudo code of the loading process is presented in Table 4.13.

Table 4.14. Pseudo code of the proposed model alternatives – loading process of first-mile trucks.

```
For truck in first-mile truck list
  If truck has finished its first-mile trip
      Add truck and arrival time step info as a pair to
        first-mile arrived-trucks list
For truck in first-mile arrived-trucks list
  If truck is not in first-mile loading trucks and loading finished trucks
    If number of loading trucks is less than maximum loading slots (10)
      Get truck's loading duration by random sampling from
        normal distribution of loading durations
      Get loading finish time step by adding truck's loading
        duration to truck's arrival time step
      Add truck and loading-finish time step info to first-mile loading trucks list
      Add truck and truck's arrival time-step info to
        first-mile waiting-for-loading trucks list
Set an empty list for loading trucks that just finished
For truck in first-mile loading trucks
  If truck's loading-finish time-step is less than or equal to time step
    Add truck to loading trucks that just finished list
      If loading trucks that just finished is not an empty list
  For truck in loading trucks that just finished
    Delete truck from first-mile loading trucks list
    Add truck to loading finished trucks
    If waiting for loading first-mile trucks are available
      Get the first-arrived truck from waiting for loading first-mile trucks list
      Get truck's loading duration by random sampling
        from normal distribution of loading durations
      If truck's cargo amount is less than its capacity
        Adjust loading duration according to the actual cargo amount of trucks
    Get loading finish time step by adding truck's loading duration
        to current time step
    Add truck and loading-finish time step info to first-mile
        loading trucks list
    Get cargo amount loaded onto wagons by summing up
        first-mile-train-station and truck's cargo load
```

At each time step the simulation checks if the freight train's scheduled departure

interval has passed. If it has, then two conditions are checked before dispatching a freight train. The first condition is whether the loaded cargo at this train station is equal to or greater than the freight train's cargo capacity. The second condition is that all first-mile trucks have finished loading their cargo and there is still some remaining cargo at this train station. If either of these conditions is satisfied, a freight train is inserted into the simulation.

The inserted freight train's maximum speed is set by sampling from a normal distribution with a mean of 50 km/hr and standard deviation of 5 km/hr. The freight train's mass and length are adjusted based on the total amount of loaded cargo. For every 2 containers the length of the train increases by the length of a wagon. If there is a single remaining container, an additional wagon is added to the freight train (e.g., 3 wagons for 5 containers). By summing the locomotive mass, tare masses of the containers and wagons, and the loaded cargo amount, the new mass of the freight train is calculated. For each freight train insertion, the number of dispatched freight train is increased by one. The dispatched freight train's ID and its cargo amount is added to the active trains list to track its journey. When a train has completed its journey, the cargo amount at the train station near the final destination (e.g., train station that is being also used as a foodmarket place) is increased by freight trains cargo amount. The pseudo code for the train insertion process and its journey tracking is presented in Table 4.14.

Table 4.15. Pseudo code of the proposed model alternatives – long-haul portion of the logistics operation done with freight trains.

```
If time step mode train depart frequency is 0
  If cargo amount at first-mile-train-station is greater than or (equal
      to train cargo capacity or cargo amount at first-mile-train-station
      is greater than 0 and number of first-mile loading trucks
      list is equal to first-mile truck count)
    Insert a train, set its speed to maximum allowed railway speed
      by sampling from a normal distribution
    Change train mass and length by the cargo loaded on to this train
    Decrease cargo at first-mile-train-station by subtracting
      cargo loaded on to this train
    Increase train count by one
    Add this train to the active trains list
For train in active trains list
  If train has arrived at its destination
    Add train to arrived-trains list
    Increase cargo-at-last-mile-train-station by cargo
      amount on the arrived train
```

For the unloading process, the simulation checks for the current number of last-mile trucks that are unloading cargo from the freight train and if there are any cargo available at the last-mile train station. As long as there is available cargo to be unloaded and number of unloading last-mile trucks is less than the maximum of 10 unloading slots, the simulation proceeds to assign trucks to the unloading process. The amount of cargo load for a given truck is determined by selecting the minimum value between the last-mile truck's cargo capacity and the currently available cargo at the last-mile train station. The unloading duration is determined by sampling from the normal distribution with a mean and standard deviation unloading durations of 45 and 5 minutes, respectively. If the assigned cargo amount for the given last-mile truck is less than its cargo capacity, then this unloading duration is adjusted according actual cargo amount. The expected unloading finish time step is calculated by adding the unloading duration to the current time step.

At each time step, the simulation checks the unloading status of the last-mile trucks. A new truck starts the unloading process as soon as an unloading slot becomes available. It is assumed that there are always trucks available at this train station. So, no delays due to waiting for the arrival of a truck for unloading is experienced (Section 4.2.3).

Once a last-mile truck has finished its unloading process (e.g., current time step is greater than the expected loading-finish time step for the given first-mile truck), the amount of cargo on the given last-mile truck is subtracted from the available cargo at the last-mile train station. If no last-mile truck has been dispatched in the last 60 seconds, then the last-mile truck with its unloading process finished, departs from the train station towards the final destination. To ensure a 60-second interval between consecutive last-mile trucks, the later truck's departure is postponed by 60 seconds. The ID and loaded cargo amount of the last-mile trucks are stored in an active-last-mile trucks list and the last-mile truck count is increased by one. The pseudo code for the unloading process and the dispatching of last-mile trucks is presented in Table 4.15.

Table 4.16. Pseudo code of the proposed model alternatives – unloading process of the last-mile trucks.

```
Get number of unloading-trucks-count
While cargo-at-last-mile-train-station is greater than 0 and
      current-unloading-trucks-count less than maximum-unloading-slots
    Get truck's unloading duration by random sampling from normal
      distribution of unloading durations
    Get truck's unloading-finish-time by adding time-step and unloading-
      duration of truck
    Get last-mile-truck-cargo-load by selecting minimum values
      between truck cargo capacity and cargo-at-last-mile-train-station
    Decrease cargo-at-last-mile-train-station by last-mile-
      truck-cargo-load amount
    If last-mile-truck-cargo-load amount is less than its cargo capacity
    Adjust unloading duration according to the actual
      cargo amount of trucks
    Get truck's unloading-finish-time-step by adding
      truck's unloading duration to current time step
Add truck, unload-finish-time-step to last-mile unloading
      trucks dictionary
For truck in last-mile unloading trucks
    If current-time-step is greater than or equal to truck's
        unload-finish-time-step
    If no truck has left in the last 60 seconds
    Insert a truck, set its speed to maximum allowed
        local speed by sampling from a normal
        distribution, change its mass by the cargo loaded on to this truck
    Add this truck to the active-last-mile trucks list
    Else
    Add 60 seconds to unload-finish-time-step and update
        given truck's last-mile unloading trucks dictionary
```

At each step the arrival status of the last-mile trucks is checked. Upon the arrival of last-mile trucks, the total transported cargo mass is increased by the cargo

amount on the given last-mile truck. The simulation loop is terminated when the total transported cargo mass is equal to the total cargo mass and all active-last-mile trucks have exited the simulation (Table 4.16).

Table 4.17. Pseudo code of the proposed model alternatives – last-mile truck arrival check and simulation loop termination condition.

```
For truck in active-last-mile trucks list
  If truck has arrived at its destination
    Add truck to last-mile arrived-trucks
    Increase total cargo mass carried by trucks by loaded-
        cargo-amount on the arrived truck
If total cargo mass carried by trucks is equal to total cargo mass and
        all trucks in the active-last-mile trucks list have left simulation
  Break simulation loop
Increase time step by 1
```

4.4. Measures of Effectiveness

In order to evaluate the performance of the alternative logistics strategies, the following measures of effectiveness have been selected: fuel consumption and duration. These metrics allow to compare the performance of alternative variations of the proposed model and the baseline logistics strategies. For testing if the differences are statistically significant or not a confidence interval of 95% is employed (unless another confidence interval value is explicitly stated) while conducting the hypothesis tests.

4.4.1. Fuel Consumption

Fuel consumption is calculated through converting different fuel types to a standardized unit of measure, called GGE. This metric, which is defined by the the U.S. Department of Energy, allows for a standardized comparison of different fuel type consumptions. GGE is also used by state and alternative fuel provider fleets for reporting compliance with EPAct requirements. At the end of a simulation run in SUMO, the

fuel consumption values are presented in mililiters (ml) for diesel and watt-hours (Wh) for electricity [119]. GGE consumption of d^{th} diesel fuel vehicle ($GGE_{diesel,d}$) and GGE consumption of e^{th} electric vehicle ($GGE_{electricity,e}$) is calculated by using Equation (4.1) and Equation (4.2), respectively [120]

$$GGE_{(diesel,d)} = \frac{ml_d \times 1.14}{3785.41}, \tag{4.1}$$

$$GGE_{electricity,e} = \frac{Wh_e \times 0.03}{1000}, \tag{4.2}$$

where ml_d is the diesel consumption of d^{th} vehicle and Wh_e is the electricity consumption of e^{th} vehicle. To calculate the final fuel consumption value in GGE unit is calculated by summing all of the GGE consumptions of all vehicles as shown in Equation (4.3),

$$GGE_{total} = \sum_{e=1}^{E} GGE_{electricity,e} + \sum_{d=1}^{D} GGE_{electricity,e}, \tag{4.3}$$

where E is the number of electric vehicles and D is the number of diesel fuel vehicles that are utilized in the logistics operations.

As mentioned in Section 4.2.3, the fuel consumption of diesel freight trains are calculated in a different manner [122]. Diesel freight train's emission class is set as "Energy" which causes the fuel consumption to be recoded in Wh electricity consumption ($E_{electric}$). The mechanical energy required for this trip ($E_{mechanical}$) with respect to electric motor efficiency ($\eta_{electric}$) is calculated with Equation (4.4),

$$E_{mechanical} = E_{electric} \times \eta_{electric} \tag{4.4}$$

The equivalent diesel-fuel energy for a diesel train (E_{diesel}), with respect to diesel motor efficiency (η_{diesel}), is calculated with Equation (4.5),

$$E_{diesel} = \frac{E_{electric} \times \eta_{electric}}{\eta_{diesel}}, \tag{4.5}$$

where E_{diesel} is converted to Joules (E_{diesel_J}), using Equation (4.6),

$$E_{diesel_J} = E_{diesel} \times 3600. \tag{4.6}$$

Diesel-fuel's energy density is approximately 36,900,000 J/L (36,900 J/ml) [121].

Using this value, the diesel fuel consumption of ($V_{diesel_{ml}}$) is calculated in mililiters (ml) in Equation (4.7)

$$V_{diesel_{ml}} = \frac{E_{diesel_J}}{36,900 J/ml}, \tag{4.7}$$

The obtained value is then converted to GGE unit, using Equation (4.1). Different levels of motor efficiencies are tested [122]. Detailed results are presented in Section 4.5.

4.4.2. Duration

In SUMO each simulation time step represents one second. For alternatives A1 and A2, the duration is calculated as the time difference between the arrival of last truck at the destination and the departure of the first truck from the origin. For alternatives A3, A4, A5, and A6, the time difference between the arrival of last truck in the last-mile trip and the departure of the first truck in the first-mile trip is calculated as the duration. This measure represents the total time of transporting all cargo from the origin to the destination for all alternatives.

4.5. Results and Discussion

In this section, the details of the case study simulation outputs are investigated. The simulation scenarios are repeated 6 times in order to address the performance variations due to stochastic elements.

A sample SUMO simulation trip output is presented in Figure 4.6. In these outputs, each vehicle that has been inserted into the simulation is saved individually. To analyze these outputs, each file has been converted to a data frame where each row represents a vehicle's journey in the simulation.

Figure 4.7. A sample of raw trip outputs of each vehicle for a tested scenario and alternative.

To calculate the total fuel consumption in a tested scenario for a given alternative, the formulas that have been explained in Section 4.4.1 are applied to the respective vehicle types. Fuel consumptions for all vehicles are converted to GGE unit and then summed up for determining the total fuel consumption for that specific scenario and alternative. The simulation outputs also contain the time-step at which a vehicle has completed its trip and exited the simulation. The maximum value among these time-steps indicates the total duration of the logistics operation. These gathered information for each simulation are stored in a separate dataframe for analysis (Table 4.17).

Table 4.18. Samples of performance metrics for tested scenarios.

Scenario-id	**Alternative id**	**Take id**	**Transport-duration**	**Total-GGE-fuel-consumption**
322	3	1	6721	741.263.538
92	1	3	61587	428.214.572
366	4	2	57789	321.720.322
73	2	4	36340	907.108.462
72	2	3	53391	750.171.629
607	6	3	84640	544.441.593
274	3	2	65601	767.057.767
171	3	1	70445	550.546.933
405	4	4	99700	963.372.706
178	4	1	54714	398.176.463

Based on the technical reports, the initial electric and diesel motor efficiencies are selected as 90% and 35%, respectively [123, 124, 125]. These values are important for converting the electricity consumption of the diesel freight train to equivalent diesel consumption and then to the GGE unit. The influence of different levels of motor efficiencies on the performance of the proposed model's variations that use diesel freight trains is evaluated in later this section.

In Figure 4.7 a box-plot is presented for visualizing the total fuel consumption, measured in GGE, for all scenarios across each logistics alternative. Each box in the box-plot summarizes the distribution of fuel consumption across all replicated scenarios. According to the results, the baseline alternative A1 has the highest fuel consumption values, with an approximate median value of 2800 GGE. The baseline variation A2 has much lower fuel consumption values compared to A1. Converting to electric trucks for long-haul operations in A2, the fuel consumption can be reduced by approximately 60%. All variations of the proposed model in generally performs much better than the baseline variations, in terms of fuel consumption. By shifting the long-haul portion of the logistics operations to freight trains, and electrifying both trucks and trains can reduce the fuel consumption levels down to 400 GGE. Therefore, as a first impression

it can be deduced that the proposed model can provide significant benefits in terms of fuel consumption.

The main drawback of the proposed model is the increased duration for transporting the entire cargo from origin to the destination. For the baseline alternatives A1 and A2, the average transportation duration is around 12 hours across all scenarios. However, for the proposed model the average duration is increased approximately 70% (19 hours average duration).

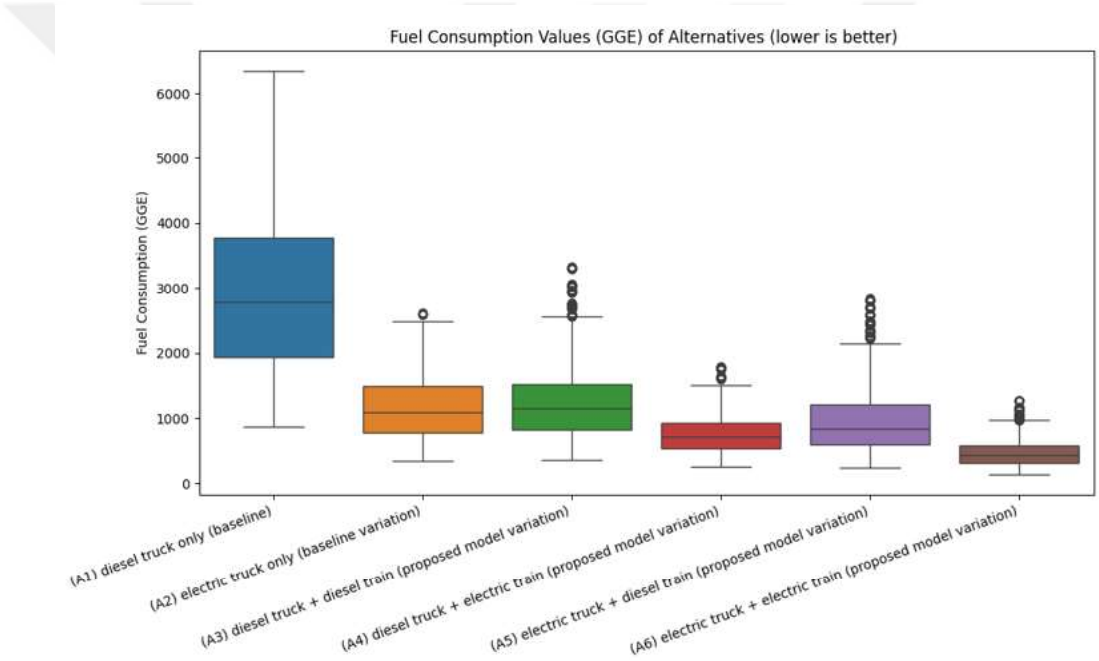

Figure 4.8. Comparison of total fuel consumption (GGE) across baseline and proposed model alternatives for all simulated scenarios.

Given the perishability aspect's importance for transporting agricultural products, selecting the adequate logistics strategy based on the cargo properties is essential. The expected increase in duration is one of the main reasons for recommending the proposed model to be employed in case of transporting only durable agricultural products (e.g., potatoes, onions, etc.). In Table 4.18 the summary of the average transportation durations for the baseline and proposed model variations are presented.

Table 4.19. Comparison of average logistics durations (hours) across baseline and proposed model alternatives across all scenarios.

Alternative ID	**Average Duration (hrs)**
A1 (Baseline)	11.98
A2 (Baseline variation)	12.41
A3 (Proposed model variation)	19.21
A4 (Proposed model variation)	19.04
A5 (Proposed model variation)	18.61
A6 (Proposed model variation)	18.59

Utilization of electric vehicles comes with the risk of battery depletion. Across of scenarios and repetitions, for any vehicle, the maximum number of battery depletions is 2 per vehicle, which have occurred for electric freight trains that travel longer than 600 km. In addition to freight trains, electric trucks also deplete their batteries at most once (1 depletion per truck) for distances over 600 km. For the freight trains each battery depletion can cause an additional duration between 1 to 8 hours, which can double given the tested battery capacity [126, 127, 128]. For trucks, significant charging technological advancements are being studied. With flash charging technology 1,000 kWh energy can be charged in 5 minutes. However, this charging duration can go up to 1.5 hours for different available charging technologies [129, 130]. According to these findings, the importance of high-capacity batteries for electric freight trains is emphasized.

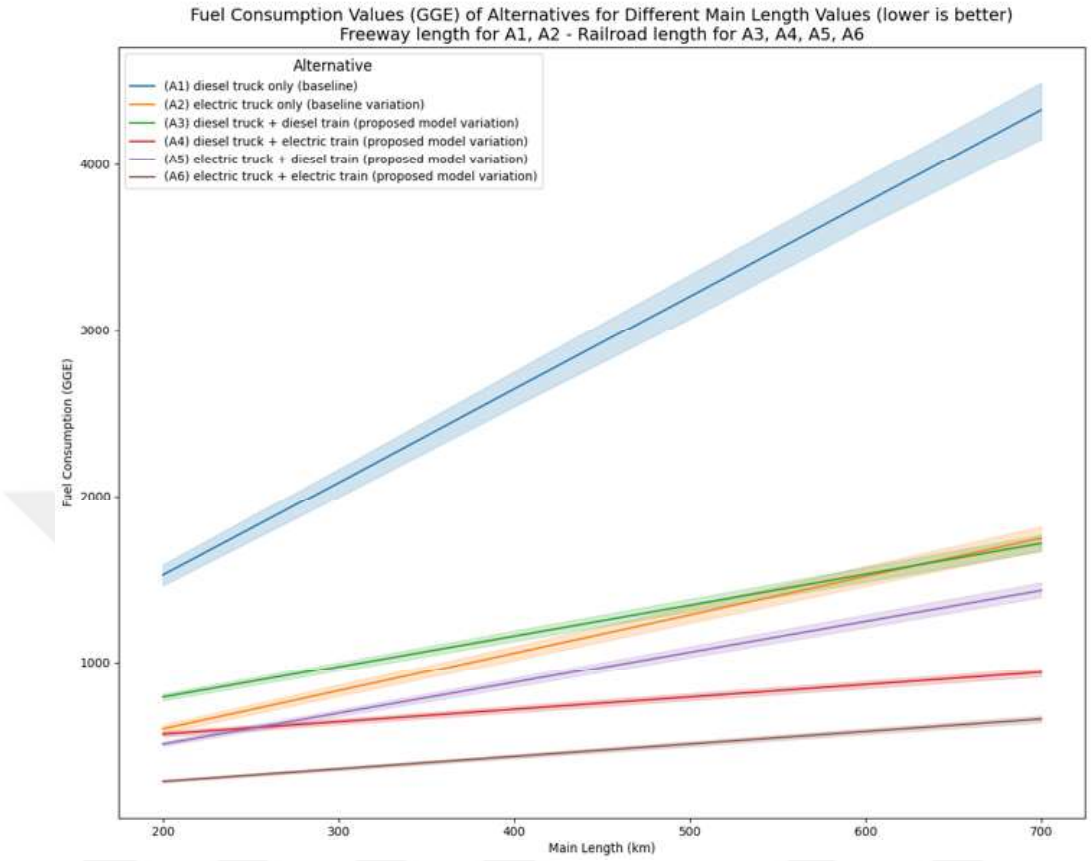

Figure 4.9. Fuel consumption levels across different main length values for baseline and proposed model alternatives.

The analyses presented thus far, show that with the proposed model, significant benefits in terms of fuel consumption can be obtained. However, there is a trade-off in terms of transportation duration. To obtain further insights, the influence of different logistics operation parameters (Section 4.2.4.3) is investigated across different alternatives.

The main distance (long-haul freeway and railroad distances) is a significant factor that influences both the fuel consumption levels and logistics durations. In the baseline alternatives, the long-haul portion of the logistics operations are done with diesel and electric trucks on the freeway. The proposed model aims to shift the long-haul portion to freight trains (electric and diesel freight trains). In Figure 4.9, the fuel consumption levels for different freeway/railroad distance values are presented.

For all tested main length values the fuel consumption of A1 has always the highest fuel consumption levels. The best performing alternative is the proposed model's variation A6 where all vehicles (trucks and freight trains) are electrified. A2 is able to perform better than the proposed model's variation A3 in which all types of vehicles are diesel fuel vehicles. However, as the main length increases the fuel consumption levels of A2 surpasses that of A3 at approximately 630 km. which can be expected due to the fact that electric vehicles are recommended to be used more for shorter trips.

A statistical test is conducted for determining if the fuel consumption difference between A2 and A3 is actually significant (p-value ≤ 0.05) after main distance length values of 600 km and more. For distances that are shorter than 600 km the difference between these two alternatives is significantly different. Another statistical test is also conducted to observe if the fuel consumption levels of A2 is statistically greater than proposed model variations A4, A5, and A6 for main length values greater than 350 km [10]. Each of these variations of the proposed model is compared individually against A2 and all results indicate that the fuel consumption levels of A4, A5, and A6 are significantly lower than A2's fuel consumption levels. These outcomes are in line with the goal of shifting long-haul transport to railway modes for distances over 350 km. However, without electrification of short-distance trucks this threshold value is expected to be much greater.

Comparing the variations of proposed models A4 and A5, when the railroad distance is greater than 250 km, the performance of A4 becomes better than A5, which indicates that the benefit of electrified freight trains becomes much clearer. All variations of the proposed model outperform the baseline alternative (A1) based on statistical tests.

It important to remember that the diesel freight trains' fuel consumptions are calculated based on predetermined motor efficiency values. Therefore, these threshold distance values may shift under different efficiency levels.

It is expected that the transportation duration increases with higher main length values. In Figure 4.9, the transportation durations across different main length values are presented for baseline and proposed model alternatives. According to this figure, for the baseline alternatives the transportation duration constantly increases with the main length. However, for the proposed model alternatives after 500 km distance values, there is a significant drop. This may have occurred due to logistics operation parameters that specifically influence the duration of the proposed model alternatives, such as freight train cargo capacity, train frequency, loading/unloading durations.

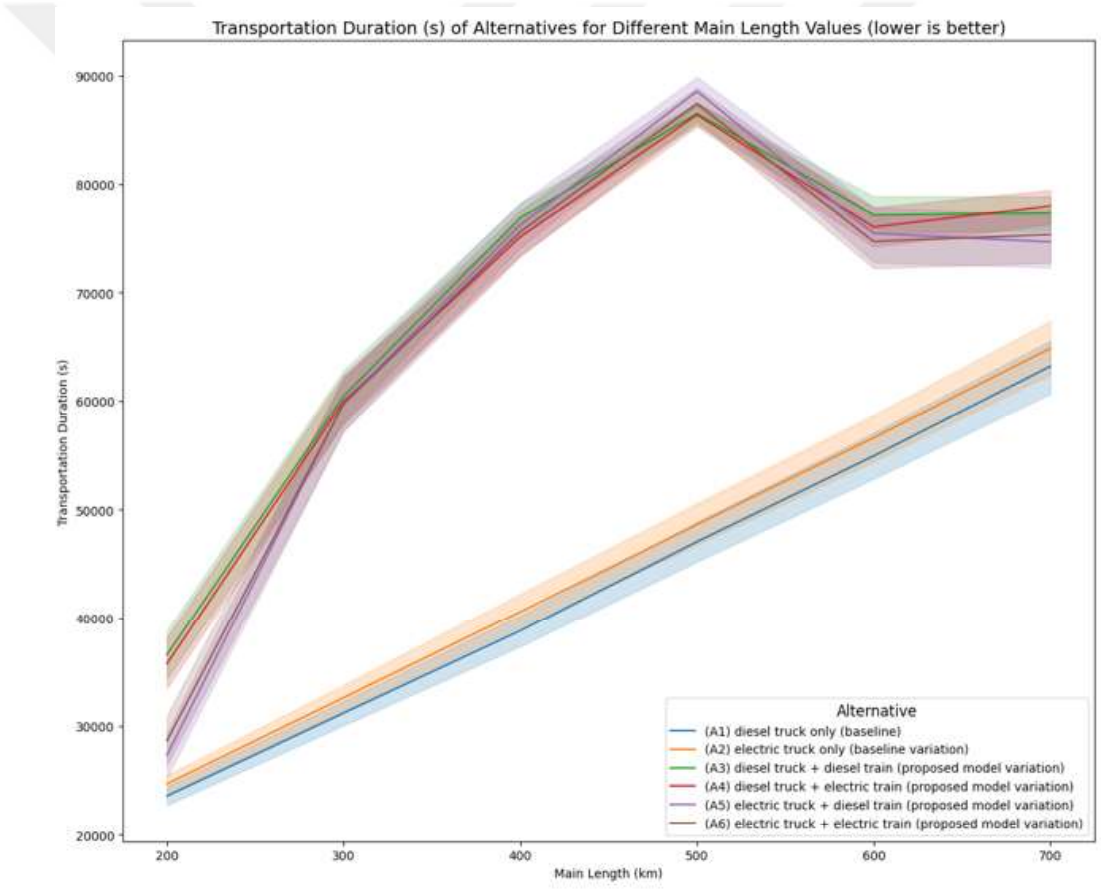

Figure 4.10. Transportation duration across different main length values for baseline and proposed model alternatives.

The statistical tests for comparing the durations of proposed model and baseline alternatives indicate that the duration differences are significant (p-value ≤ 0.05) for all tested main length values. Further analysis is necessary for better understanding

the effect of logistics operation parameters on the transportation duration for all alternatives. With the obtained insights, factors that influence the duration dynamics can be identified. Recommendations according to these outcomes can be provided for both logistics experts and policymakers.

The effect of cargo mass on the fuel consumption and transportation duration levels of baseline and proposed model alternatives are investigated. According to the results in Figure 4.10, as the total transported cargo mass increases, the fuel consumption levels increase as well for across all alternatives. Similar to previous results, the highest and lowest fuel consumption levels are observed for A1 and A6, respectively. Additionally, the fuel consumption levels increase more rapidly for A1 compared to every other alternative. Another detail is that for cargo masses greater than approximately 550 tons, fuel consumption levels of A3 overtakes that of A2. The difference between these two alternatives is statistically significant (p-value ≤ 0.05) for cargo masses of 500 and 700 tons. The fuel consumption levels difference between A6 and A4 are statistically significant for all values of cargo mass.

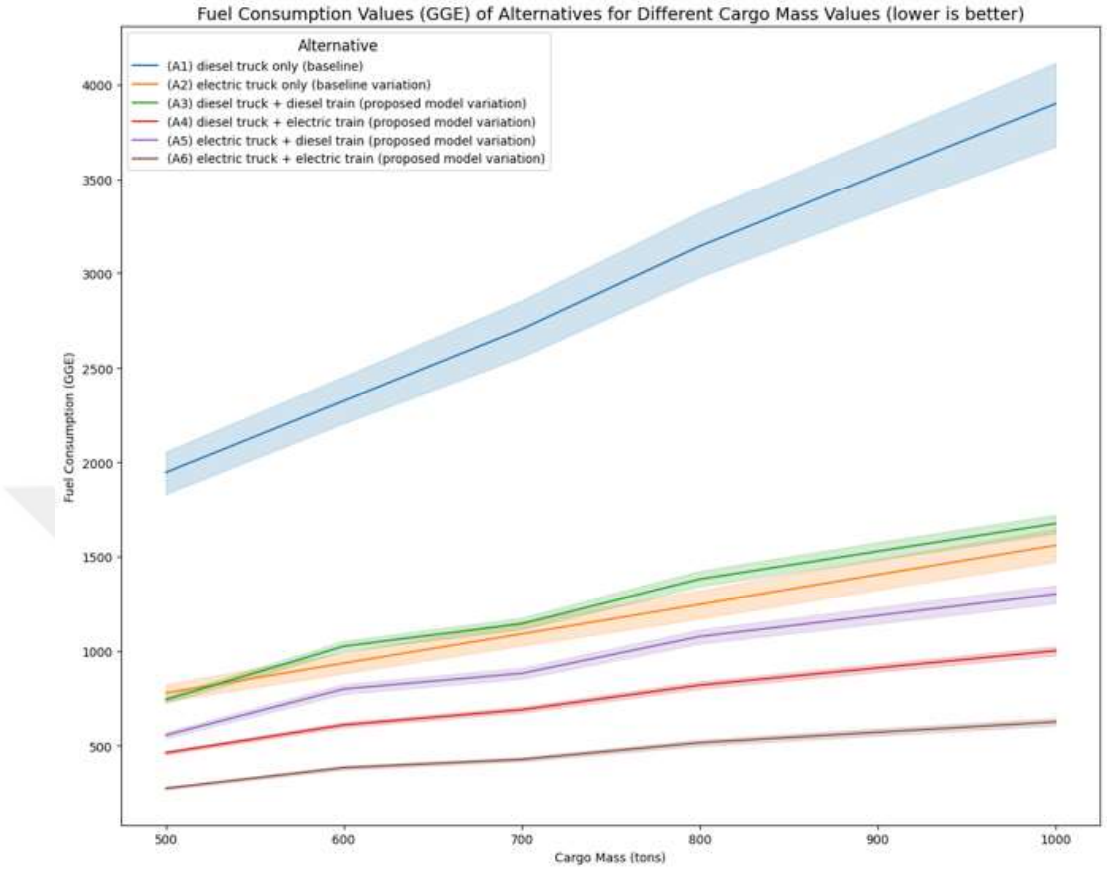

Figure 4.11. Fuel consumption levels across different cargo mass values for baseline and proposed model alternatives.

Investigating the duration variation for different cargo masses (Figure 4.11) indicates that the baseline alternatives increase steadily with the cargo mass values. The statistical tests confirm that incremental increases in transportation duration for the baseline alternatives are statistically significant (p-value ≤ 0.05) between consecutive tested cargo mass values.

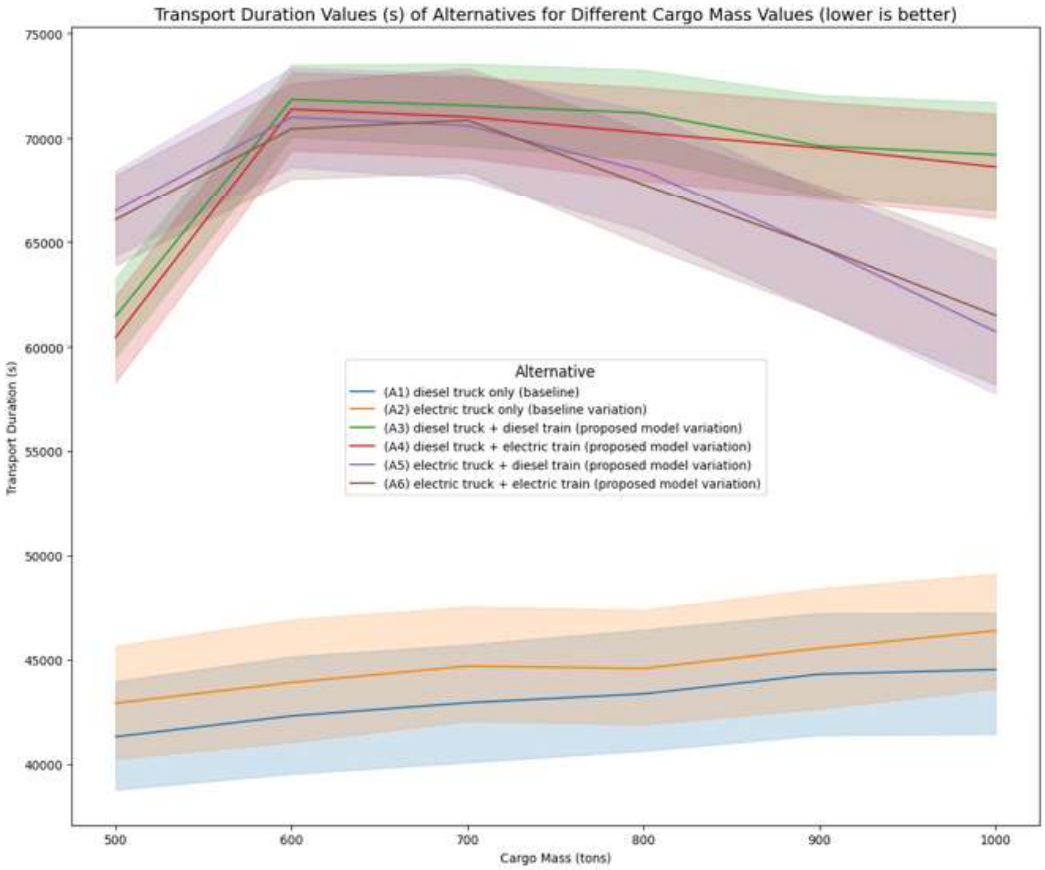

Figure 4.12. Fuel consumption levels across different cargo mass values for baseline and proposed model alternatives.

In contrast, for the proposed model alternatives, there is no clear trend between the transportation duration and the cargo mass. These alternatives all have similar transportation duration patterns for different cargo values. The statistical tests show that the duration variations are statistically insignificant ($p > 0.05$) for each cargo mass values. It can be concluded that the higher cargo capacity of freight trains is the root cause for this benefit. Furthermore, changing the vehicle type (electric and diesel) does not influence the transportation duration in a significant manner.

For the proposed model, the freight train departure period and cargo capacity are parameters that affect only the alternatives of the proposed model. In Figure 4.12, the transportation duration for different departure values is presented. As the freight train's departure period increases, the transportation duration also increases. The

tested train departure period values are 0.5, 2 and 4 hours.

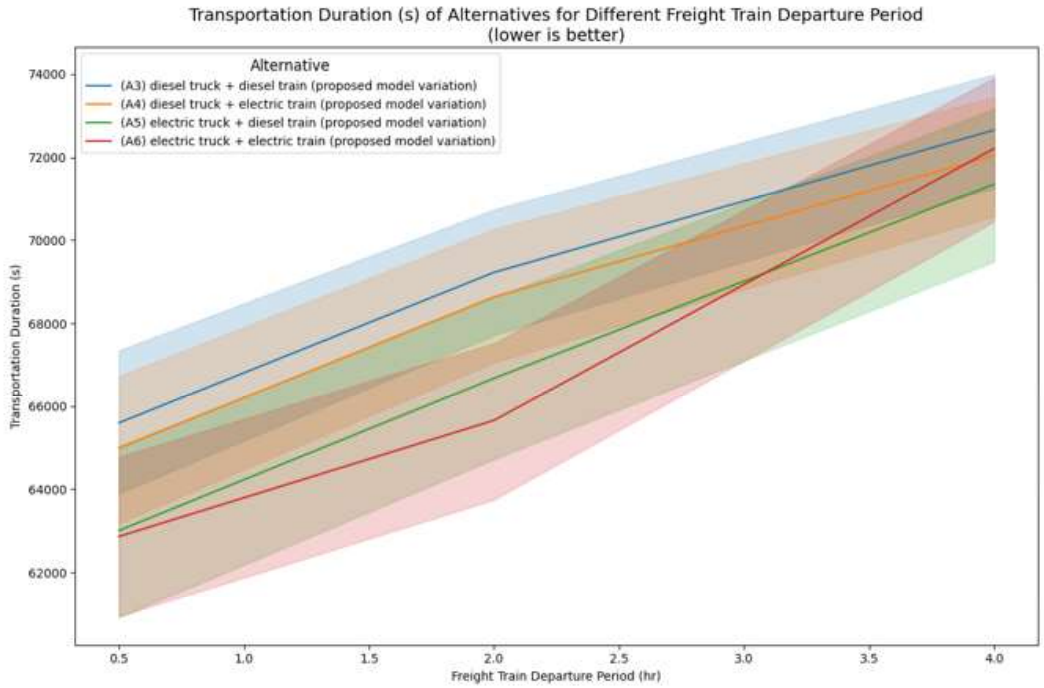

Figure 4.13. Transportation duration across different train departure period values for the proposed model variations.

According to the pairwise statistical t-test results between different period values, there is a significant difference of transportation duration for all tested period values. This indicates that higher train availability significantly benefits the proposed model's transportation duration aspect.

In Figure 4.13, the relationship between different freight train cargo capacities and transportation durations is presented. According to the figure increasing the cargo capacity may result in shorter transportation durations. For the tested values (250-, 500-, and 1000-tons cargo capacity) pairwise statistical tests are conducted to observe significant benefits can be obtained. Based on the test outcomes, significant reduction in transportation duration can be obtained by increasing the cargo capacity from 250 tons to 500 tons and 1000 tons. However, when comparing capacities of 500 and 1000 tons, the results indicate that the average duration difference is statistically insignificant.

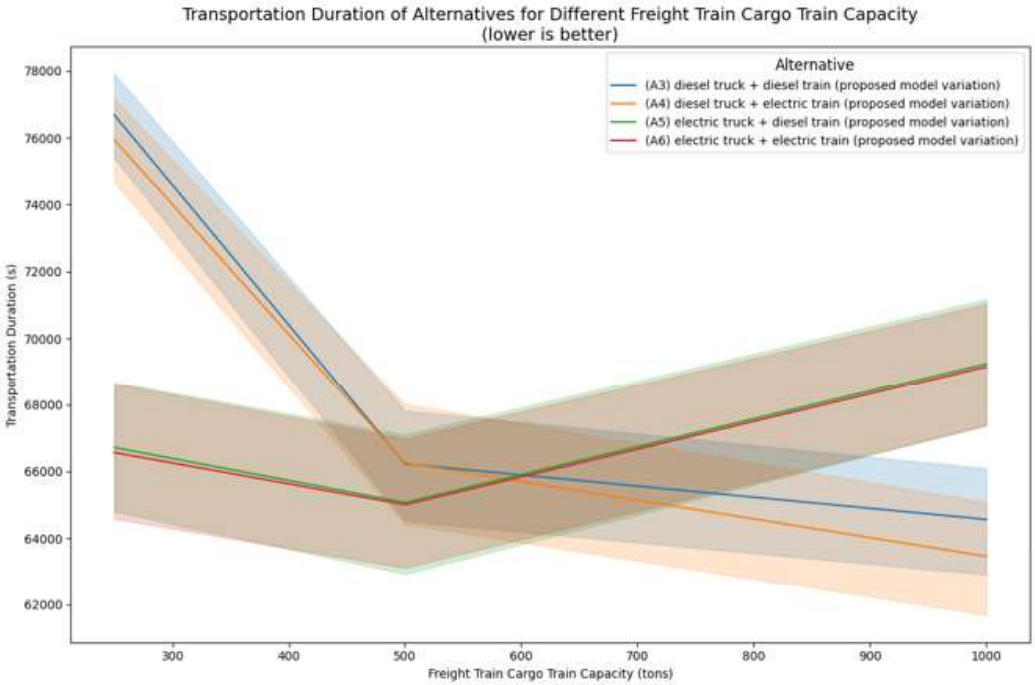

Figure 4.14. Transportation duration across different freight train cargo capacity values for the proposed model variations.

According to these outcomes, initially increasing the cargo capacities of the freight trains can provide benefits in transportation duration. However, after a certain threshold the potential gains may diminish significantly. Factors such as cargo mass, loading/unloading durations and other logistics operation parameters needs to be considered.

In addition to duration benefits, fuel consumption values can also be improved by increasing the cargo capacity of the freight trains (Figure 4.14). Increasing the cargo capacity of these freight trains decreases the number of required trains for handling the long-haul portion of the logistics operation. Subsequently this leads to lower fuel consumption levels. For all train types, the reductions of fuel consumption levels are statistically significant. However, the obtained benefits are much higher for diesel freight trains compared to electric trains. In addition to fuel consumption reduction, infrastructure maintenance costs can also decrease by reducing the number of trains.

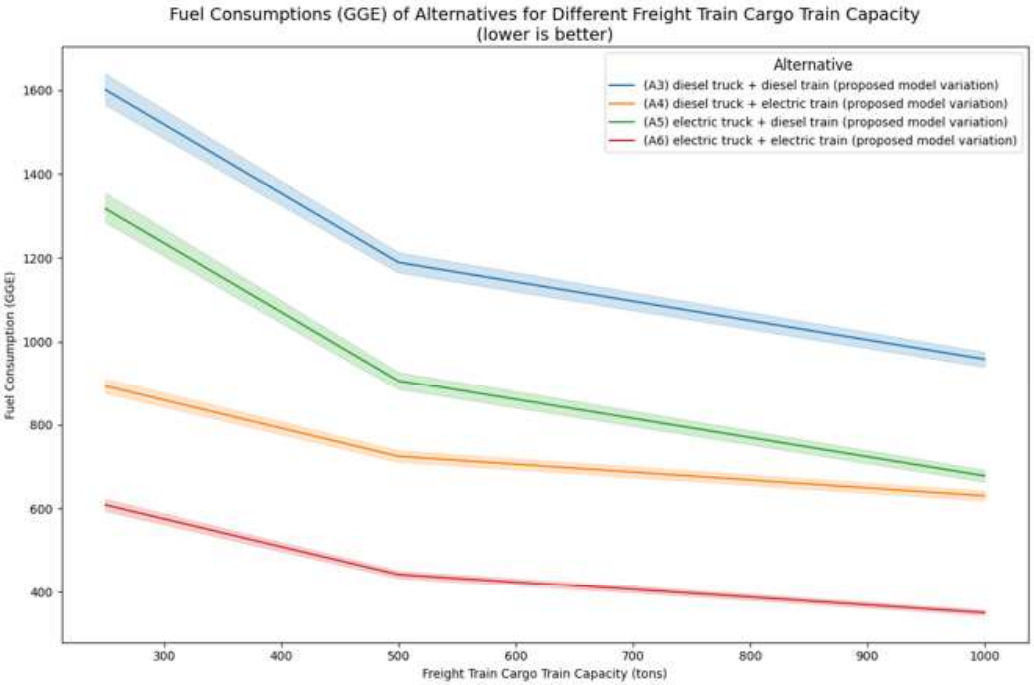

Figure 4.15. Fuel consumption levels across different freight train cargo capacity values for the proposed model variations.

The influence of local road lengths is investigated through statistical analyses. With longer local road lengths the transportation durations are expected to increase. The trucks in the baseline alternatives take longer to reach the freeway to start the long-haul portion of their trip. For the proposed model, the duration is expected to decrease with shorter lengths, as trucks can start their loading operations earlier.

According to the data presented in Table 4.19 the local road lengths is statistically significant on the transportation duration values for the proposed model alternatives, and insignificant for the baseline alternatives. These results indicate that the trucks in the baseline alternatives are not affected by the local road lengths, in terms of transportation duration. However, providing train stations near the OD points can provide significant transportation duration benefits for the proposed model alternatives. By reducing the local road distances between the farm and train station, and train station and final destination, from 40 km to 20 km, the overall transportation durations can decrease up to an hour. By providing shorter connections to the train stations,

the loading and unloading processes can start much quicker. Given the fixed schedules of freight trains, it is important to start the loading process as quickly as possible to avoid missing train departures.

Table 4.20. T-test results for each alternative for comparing the tested local lengths' influence on the transportation duration.

Alternative ID	**p-value**
A1 diesel truck only (baseline)	0.21
A2 electric truck only (baseline variation)	0.17
A3 diesel truck + diesel train (proposed model variation)	1.618×10^{-24}
A4 diesel truck + electric train (proposed model variation)	9.336×10^{-27}
A5 electric truck + diesel train (proposed model variation)	3.112×10^{-71}
A6 electric truck + electric train (proposed model variation)	2.263×10^{-76}

As mentioned at the beginning of this section, the motor efficiency values are selected as 90% for electric motor and 35% for diesel motor. Technical reports show that the efficiency levels can vary between 30% and 40%, and 85% and 95% for diesel and electric motors, respectively [123, 124, 125]. A heatmap is developed with a sensitivity analysis to compare the ratio of 1000 kWh electricity consumption of a fully-electric freight train and 1000kWh fuel consumption of a diesel train that has been modeled as an electric train (Figure 4.15). Both consumptions are converted to GGE unit to be compared. Equation (4.2) is used for converting the electricity consumption of electric freight train to GGE unit. For the converting the fuel consumption of the diesel freight train to GGE unit, the equations between Equation (4.4) and Equation (4.7)are used. Selecting the previously mentioned efficiency levels (35% diesel motor efficiency and 90% electric motor efficiency) shows that electric trains consume 40% of the fuel that has been used by the diesel freight trains. For example, with these fuel efficiency levels and for the same electricity consumption values, if a freight train has consumed 1000 GGE of fuel, the expected consumption value for electric train is 400 GGE. The influence of these motor efficiencies on the critical long-haul distance values are investigated.

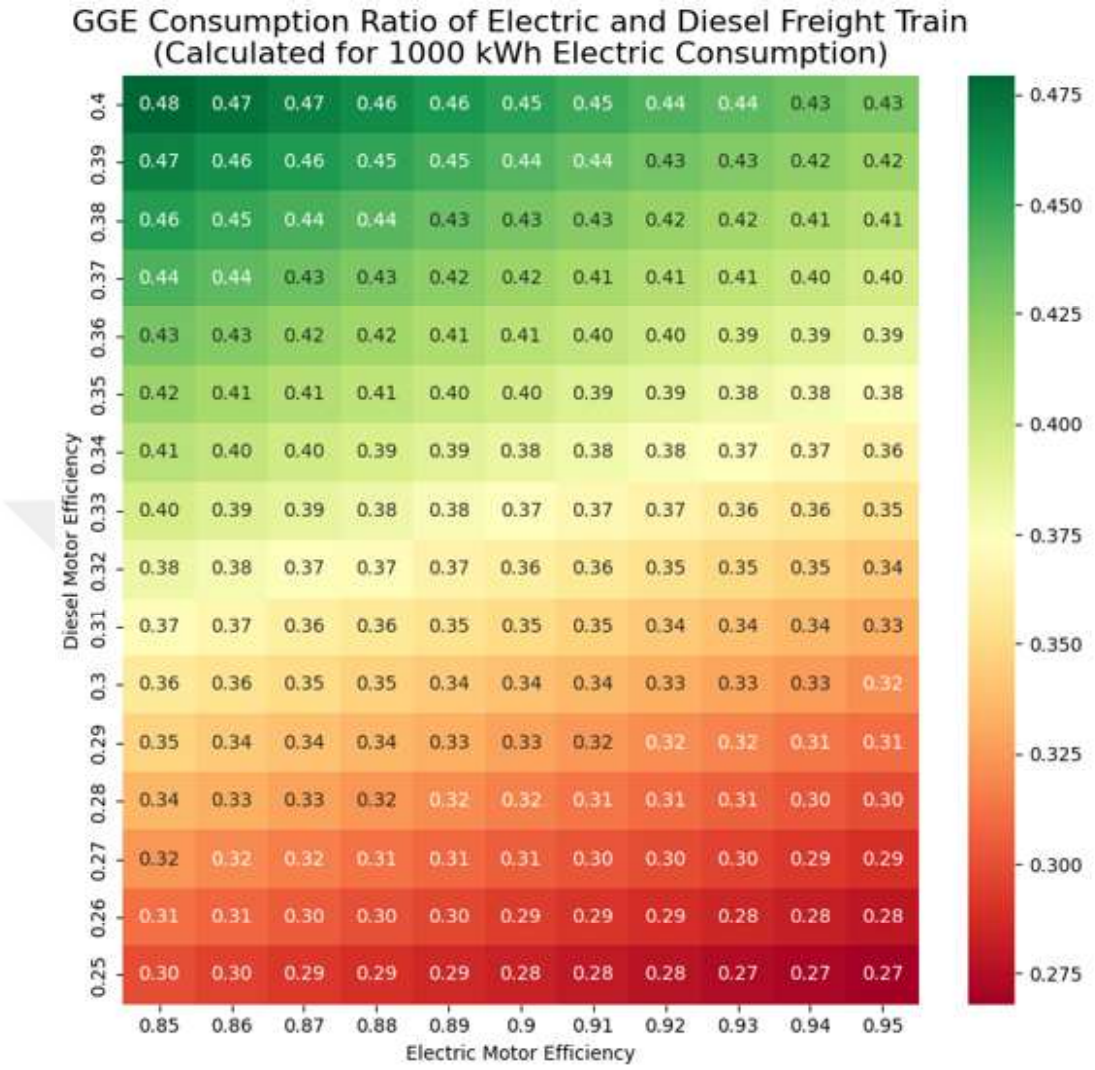

Figure 4.16. GGE consumption ratios of diesel and electric freight trains for different electric and diesel motor efficiencies.

For different ratios the performance of proposed model's alternatives A3 and A5 for tested scenarios are re-calculated with new freight train fuel consumption values in GGE units. Based on the sensitivity analysis, it is determined that as the diesel to electric motor efficiency ratios decrease, the proposed models with freight trains start to converge with the performance of the baseline approach with electric trucks at longer long-haul operations (Figure 4.16). According to the results at least a ratio of 35% is recommended for shifting to the proposed model with the diesel freight trains and not using electric trucks. At a ratio of 45% A5 can outperform A4 for distances shorter than 450 km. This indicates that for cases with relatively low electric motor

performance and high diesel motor performance, electrification of the freight trains is not always necessary.

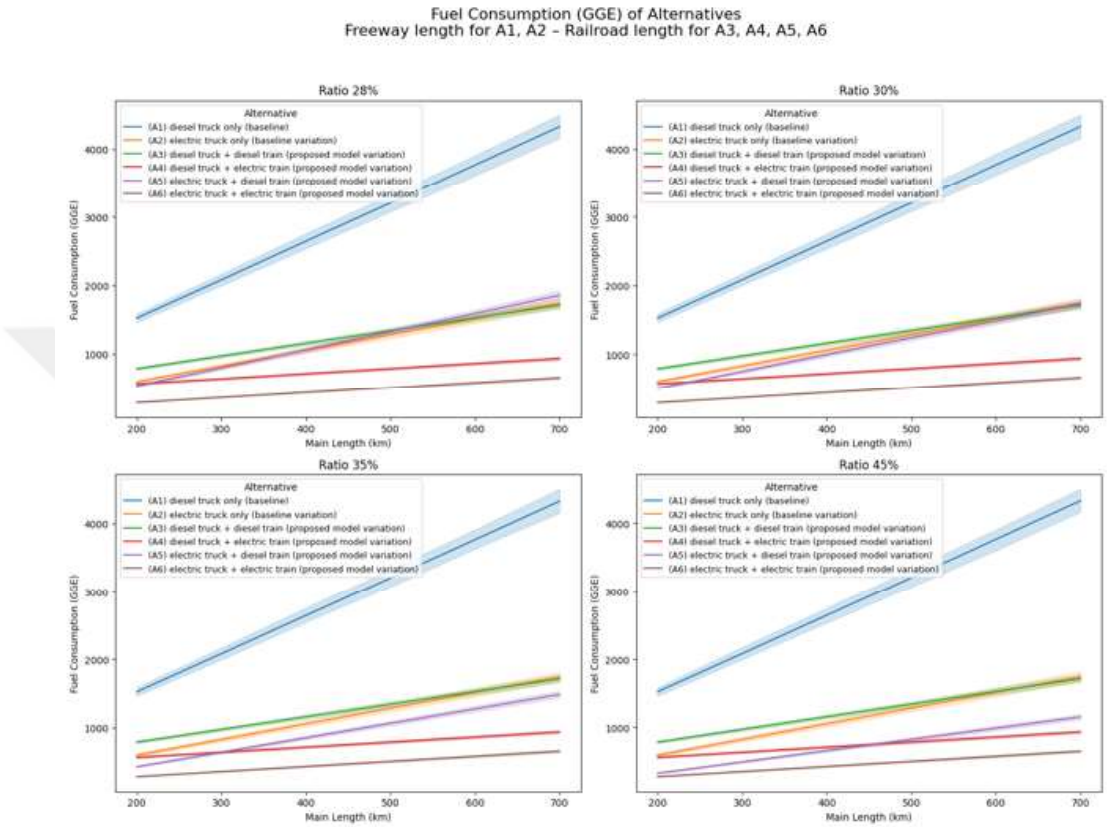

Figure 4.17. Influence of diesel to electric motor efficiency ratios on the performance of alternatives for different lengths.

5. POLICY IMPLICATIONS

Logistics operations of agricultural products is a very sensitive topic due to food product's price inelasticity [131]. This means that even high transportation costs can be reflected in consumer prices. However, the effect of increased price gap (Table 1.1) does not impact the demand significantly. Therefore, optimization of food logistics systems is more than just an economic concern. Food affordability and security, sustainability, and overall well-being of a nation's population are all important aspects that need to be considered while designing new solutions.

Increasing the logistics fleets' share of low-emission vehicles with alternative fuel sources and designing innovative logistics strategies are common topics for optimizing the logistics systems. However, most proposed solutions and developed concepts fail to consider the practical constraints of the studied logistics system. For example, electrification of entire fleets of vehicles may provide significant benefits from the perspective of environmental costs of transportation field. However, the required energy for these vehicles and the need of new infrastructure (i.e., charging stations, maintenance hubs, etc.) can be a significant financial load, especially for limited resources. For concepts such as synchromodality offer significant benefits in theory but its practical implementation faces significant challenges. According to the interviews with logistics experts, economic status of the country, limited infrastructure, and the working culture are some of the barriers. Especially logistics professionals working in developing countries, consider these innovative concepts nearly impossible for real-life applications [101]. Compared to developed countries, the developing economies have much more limited resources for implementing concepts and developing projects. Therefore, for this type of countries, more pragmatic approaches must be employed.

Maximizing the effective use of the available infrastructure must be prioritized instead of consuming the limited resources for constructing entirely new systems. This requires close cooperation between the policymakers and logistics experts. For exam-

ple, Antalya, which is a leading city in TC in terms of greenhouse cultivation subject, provides a relevant case study. According to logistics experts' interviews, numerous trucks are dispatched daily from Antalya to distribute the food products across the country [101]. Policymakers should promote and incentivize shifting logistics operations from less efficient and high-emission trucks to efficient and sustainable freight trains for distances over a certain threshold. The main idea is to maximize the leverage of each transportation mode's strength for the appropriate portion of the logistics operation (i.e., trains for long distance, trucks for short distance) [4, 92]. This can be achieved by providing train stations where loading operations can be conducted, frequent freight train dispatches, and higher cargo capacities. To provide these incentives effectively for both long- and short- term planning, logistics experts should share their planning details with policymakers. For short-term planning (e.g., next 2-3 days) the logistics experts can provide detailed information about their operations, which enables the policymakers to adjust train schedules and cargo capacity accordingly. In the long term with the data collected from logistics experts, policymakers can make use of AI and other technologies to identify patterns and predict future demands. This approach will allow the optimal allocation of the limited resources for improving or expanding the available infrastructure (i.e., new railroads, train stations, low-emission vehicle investments). Furthermore, the role of logistics hubs associated with sustainable transportation modes must be redefined. For instance, train logistics hubs can also function as food marketplaces. Increasing the role of sustainable transportation elements (i.e., vehicles, origins and destinations) can provide further economic, environmental and social benefits.

Historically, train stations have been generally built at the edges of a city. As cities develop, the attraction power of these train stations has caused the new urban sections to grow around these important hubs [132]. Their importance from a city planning perspective has always been significant. These structures have served as gateways that connect national and international cities. Additionally, train stations are essential for cities to join the national system [133]. Haydarpaşa and Sirkeci Terminals in Istanbul, Grand Central Terminal in New York City, Musee d'Orsay in Paris, Hauptbahnhof

in Berlin, and Atocha Station in Madrid are examples for demonstrating how train stations are more than just transportation hubs for their cities. These stations have acted as cultural, social, and economic hubs with their art galleries and exhibitions, libraries, cafes, restaurants, and retail stores. Some of these stations have inhabited botanical gardens or transformed into museums (Figure 5.1). The proposed model takes advantage of the centrality and attraction power of the train stations. With relatively low investments compared to entirely new projects, significant benefits can be expected by increasing the role of these points within food transportation operations. This enhances the overall benefits of shifting to a more sustainable transportation model.

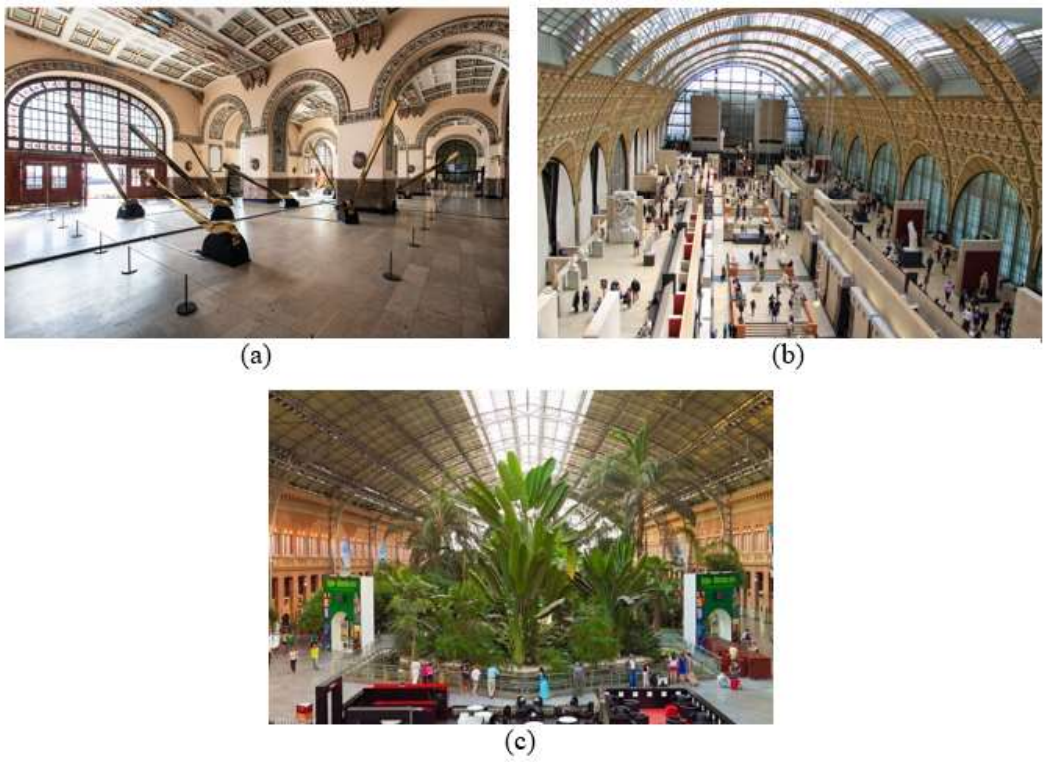

Figure 5.1. Examples of train stations in Haydarpasa Station in Istanbul (a), Gare d'Orsay in Paris (b), and Atocha Station in Madrid (c) being used as more than just transportation hubs [134, 135, 136].

Innovative concepts that offer theoretical benefits, such as synchromodality, must be supported by practical solutions that have been validated by logistics experts and policymakers. According to the literature review (Section 3.1) and discussions with lo-

gistics sector experts, the concept of synchromodality is generally considered as a vague and non-practical concept [101]. From the agricultural logistics perspective, the perishability of goods, limited availability of real-time data from various sources, privacy concerns and the limited financial resources make this concept especially challenging in terms of its practicality for developing countries. Therefore, in addition to all available logistics stakeholders, the involvement of state authorities and policymakers is essential for the implementation of this planning concept.

In this dissertation a new definition for the concept of synchromodality is proposed. Using this new definition, proposed model named, ALIS (Agricultural Logistics for Intelligent Sustainable) synchromodal logistics system is developed and tested in a case study. The results of this developed system show that significant economic and environmental benefits can be obtained. The main idea of this system and the proposed synchromodality definition are discussed and validated with logistics experts. The proposed definition is as follows:

Synchromodality is the coordinated short- and long-term planning of logistics operations and the roles of transportation infrastructure elements. Cargo properties, economic resource availability, and sustainability and climate-change objectives are the main aspects behind these planning processes. Policymakers and logistics experts jointly promote and incentivize the use of more efficient transport modes and adjust the role of associated infrastructure elements (e.g., origins, destinations). The main aim is to minimize cost, fuel consumption, and emissions levels, while maximizing the collection of operational data and the traceability of transported cargo.

6. CONCLUSION AND FUTURE WORKS

The price hike during the farm-to-fork journey of the agricultural products is a significant issue. Logistics costs and intermediary stakeholders are among the main reasons for this by this unsustainable problem which effects both producers and consumers. Therefore, efficient, sustainable, and practical solutions for improving the performance of agricultural logistics system are essential. The strengths of each transportation mode must be made use of properly. Additionally, for developing countries, maximizing the utilization of the available transportation infrastructure capacity with efficient transportation modes is crucial for achieving satisfactory performance outputs.

In this dissertation an agricultural logistics strategy called ALIS synchromodal logistics system is designed on a proposed definition for the synchromodality concept. This system integrates road and railroad transportation modes for obtaining economic and environmental benefits with lower price differences between the farm and the fork, fuel consumption, and emission levels. The first- and last-mile portions are handled with trucks and the long-haul portion of the logistics operation is conducted with freight trains. An important aspect of this system is the proposed that utilization of train stations as food marketplaces so that the additional trips from the train stations before reaching its final destination are eliminated (e.g., supermarkets or warehouses). Both fossil and alternative fueled (e.g., electric) vehicles (e.g., trucks and freight trains) have been tested across different scenarios and its performance is analyzed. In total 2 baseline alternatives (use of only diesel and electric trucks for entire transportation) and 4 proposed model alternatives (combined use of diesel and electric trucks for first- and last-mile trips, and diesel and electric freight trains for the long-haul portion) are tested across 144, and 648 scenarios, respectively. According to the results proposed model's alternative A6 can provide up to 70% reduction in fuel consumption compared to baseline alternative A1. For lower distances the baseline alternative A2, can outperform the proposed model's alternative A3. As higher distances the results are reversed for these two alternatives. According to statistical tests, for A4, A5, and A6 the difference

of fuel consumptions, compared to A2, is significant for long-haul distances over 350 km, which is in line with the of EU's green deal goal of shifting to railroad transportation for distances that are greater than 350 km. However, the proposed model does cause a trade-off in terms of transportation duration, which can be a significant problem for highly perishable products.

According to the performance of ALIS synchromodal logistics system and interviews with experts from the logistics sector, a new definition for the concept of synchromodality is presented. Current definitions of this concept are generally considered as abstract and difficult for real-life implementation by the logistics experts. This new definition addresses the issues of the available definition and is tested with a logistics system that has been designed based on this new definition.

The designed system is tested in SUMO environment which is an open-source and flexible traffic simulation tool. Logistics simulation studies conducted with open-source tools are very limited. Most of the studies in the literature do not share their methodologies for modeling their simulation environment and for studies conducted in SUMO this is even more evident. This dissertation serves as a guide on how to model electric trucks, diesel and electric freight trains in an open-source simulation environment in a detailed and replicable manner.

The proposed model has been tested on a very simple simulation network to evaluate the performance of the developed ALIS synchromodal logistics system as clearly as possible. Additionally, the effect of different levels for the share of electric and diesel vehicles and the battery charging aspects are not covered in this dissertation. More complex logistics operation cases must be studied in future studies.

In summary:

(i) The need for robust, efficient and sustainable food supply chains is at an all time high due to oil price fluctuations, price hikes between the producers and

consumers, and food affordability and security concerns. Studies in the literature are trying to develop new solutions and concepts for providing innovative solutions that can provide significant economic and environmental benefits. However, majority of these solutions and concepts are considered as impractical by logistics sector experts due to the fact that these studies often ignore real-life constrains. These solutions are even more difficult to implement in developing countries with limited resources. Therefore, the ALIS synchromodal logistics system has been proposed based on a new definition of the synchromodality concept. This new synchromodality definition has been validated by logistics experts and the performance of the proposed system. The methodology of this dissertation can be especially useful for policymakers and sector experts that are looking for practical solutions that considers the real-life constrains and promotes the efficient utilization of available infrastructures, instead of constructing entirely new projects.

(ii) Instead of constructing entirely new infrastructure projects or renewing entire logistics fleets with alternative energy sourced vehicles (e.g., electric vehicles), this system promotes the effective utilization of the available infrastructure by maximizing the share of efficient and eco-friendly transportation modes, such as freight trains. This approach allows this system to be much more applicable in practice, which has also been validated with logistics sector experts [101]. This dissertation acts as a guide for both sector experts and policymakers, especially for times in which food affordability and security are becoming very important topics in the near future.

(iii) Policymakers can benefit from this dissertation which proposes practical solutions for improving the food affordability and security issues. Actions taken to resolve the food affordability issue can gain public support which is beneficial for public well-being. Practically applicable solutions for developing countries that enhances food security can be achieved through utilizing the transportation infrastructure, such as railway networks and freight trains, which can improve the traceability of the food cargo. This dissertation can serve as a guide for implementing these solutions in practice.

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