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Developing an Optimization Model for the Mixed Fleet Electric Vehicle Scheduling Problem (MF-EVSP)

Cycle-Based Scheduling Model

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Summary

The primary objective of this work is to introduce a Mixed-Integer Linear Programming (MILP) model for the Multi-Fleet Electric Vehicle Scheduling Problem (MF-EVSP), incorporating a cycle compression approach. This model defines a unified transport system that integrates buses utilizing diverse energy sources.

In order to reduce deadhead kilometers, the suggested model includes crucial features like real-time battery tracking, effective route assignment, and optimized depot assignment. The research successfully illustrates the operational capabilities and benefits of managing both defining and developing heterogeneous fleets through these assessments. The evaluation was conducted through a test using generated city and line data, tailored to the real-world scenario of Torino.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Given the pressing challenges by climate change the intention of implementation of energy transition in public transport in the recent years have one of the more important steps. Historically, diesel-powered vehicles have constituted the majority, and in some cases, the sole source, for meeting urban transportation demands. Their use result in high emissions of pollutants as carbon monoxide(CO), sulfur dioxide (SO_2), nitrogen oxides (NO_x, and particulate matter (PM_{10}) and ($PM_{2.5}$)[1] . Around the 25% of CO_2 emissions from road transportation are caused by heavy-duty vehicles, such as trucks, buses, and coaches[2].

Moreover, the use of this traditional-diesel diesel-vehicles considerate health impacts, noise pollution and their mentioned contribution of greenhouse gas emissions. Consequently, exist a growing imperative to transition for technologies of lower emissions transport, especially from the options that affront some of the consequences of use diesel vehicles. The European Union has set an ambitious target to reduce CO_2 emissions from buses by 90% by 2030 [3].

For arrive to cities with less emissions in the transport system, the implementation of different technologies are under investigation and present in some initial cities. Some of this vehicles are the diesel-electric hybrids, Battery electric vehicles(BEVs), and various natural gas and bio-fuel options such liquefied natural gas(LNG), propane(LPG), compressed natural(CNG), and bio-diesel blends [1]. Between this options the electrification contemplate a promising solution due to high efficiency, expanding infrastructure, potential for reduced operational cost expenses and zero tailpipe emissions [4]. However, the implementation of BEVs considerate their own complexities, as charging limitations and range constraints [5].

The present work is focuses on the Multi-Fleet Vehicle Scheduling Problem (MF-EVSP) inspired in transport systems that aims to use different vehicle sources for feed the demand. The problem selected considerate general public transport constraints and electric vehicle characteristics. Many cities are transitioning progressively, maintaining a mix of diesel, natural gas, and electric vehicles due to factors such as higher initial costs [6]. Some examples are Milan(Italy), Berlin(Germany), Torino(Italy) and Madrid(Spain) that considerate electric, diesel, natural gas and in some cases hydrogen energy source in their vehicles.

The objective of this work is formalize a mathematical model for the MF-VSP and tested using thought cities scenarios. Also is modeled thought some lines, as simple case, with the actual information of Torino, Italy. This model is used for minimize the operational deadhead costs and maximize the use of less-emissions vehicles.

Chapter 2

Literature Review

Optimization in public transportation involves various strategies to achieve cost reduction and emission mitigation objectives. In the past years, the use of diesel and Compressed Natural Gas (CNG) vehicles enabled the development of fundamental operational characteristics as a basis for improving the public transport system. Table 2.1 presents a selection of research related to the Vehicle Scheduling Problem (VSP) and other problems focused on minimizing operational costs. Given the specific characteristics of the system under study, the consideration of multiple depots is essential to evaluate their contributions effectively.

To accomplish the minimization of the cost target, the segments unpaid as the non-passenger kilometers, are considered constant as a point of study. Characterized by instances for pull-in, pull-out, and distances between the ending points of the before trip for the starting point of the following trip. Some approaches for addressing this type of cost-related research by [9] and Prakash et al. [7], optimizing the allocation of vehicles to depots based on starting and ending costs. Eliiyi et al. [9] further expanded on this by considering passenger satisfaction and demand. Extending the problem, Macini et al. [14] developed models that incorporate vehicle heterogeneity, including diverse capacities, hourly costs, and other characteristics.

Each author adopts distinct approaches to analyze and address public transport problems concerning depot assignment or scheduling. To compare and describe the constraints of the research presented in Tables 2.1, 2.2, and 2.3, the following points are considered:

1. Each Trip is run by just one vehicle
2. Each depot has a limited number of vehicles
3. Each vehicle return to the same depot from which it started
4. The total time during which a vehicle is away from its depot is limited to a pre-specified time

Authors	Journal(year)	Problem	Method Used	Fleet	Dead km
Prakash et. al.[7]	EJOR(1999)	MD-VSP(parking depot)	Not nominated solutions	Hom	✓
Mahadikar et. al.[8]	JAT(2015)	MD-VSP(allocation to depots)	MILP; Brach and cut method	Hom	✓
Eliiyi et. al.[9]	Elsevier(2012)	MD-BSP	Fuzzy parametric approach	Hom	✓
Narashimha et. al.[10]	Swarm Evol. Comput.(2013)	MD-VRP	Ant Colony	Hom	✓
Haghani et. al.[11]	Tranps. Res(2002)	MD-VSP;MD-VSRTP	Heuristic approach	Hom	✓
Salhi et. al.[12]	COR(2014)	MD-VRP	Formulation & variable neighborhood search	Het	-
Olariu et. al.[6]	Procedia Comput. Sci.(2020)	MD-VSP	Heuristic	Hom	-
Willoughby et. al.[13]	Omega(2002)	MD-BDMP(allocation to depot, multi period)	Mixed Integer Programming(MIP)	Hom	✓
Mancini et. al.[14]	Transp. Res. Part C Emerg.(2015)	MD-VRP(multi period)	Adaptative Large Neighborhood Search based Matheuristic	Het	-

Table 2.1: Overview of Research on Vehicle Scheduling and Dead Mileage Considerations

5. Limited number of vehicles of one type
6. Depot feasibility for the vehicle
7. Maximum general length of time constraint
8. Feasibility Constraints
9. Battery constraints
10. Electric charger disposability
11. Limited peak of energy for charge in the station

The constraints enumerated include a preliminary general constraints (1)-(4) for [11]. This is included with or without of electric vehicles. Then the constraint (5)

Author	Journal (year)	Problem	Method Used
Wang et. al.[4]	Energy (2024)	MD-(E)VSP (limitation in charging facilities)	Adaptive Large Neighborhood search
Yao et. al.[15]	SCS (2020)	MD-EBSP (multiple vehicle types)	Genetic Algorithm
Zhang et. al.[16]	Int. J. Sustain. Transp. (2022)	EBSP (Partial mixed route strategy and partial recharging)	Adaptive large neighborhood search
Cui et. al.[17]	Transp. Res. E Logist. Transp. Rev (2023)	Mixed Fleet Vehicle Scheduling Problem (MF-VSP) and Charging Scheduling	Mixed Integer Programing Problem
Olsen et. al.[18]	Cent Eur J Oper Res (2022)	MD-VSP(Multi Fleet)	Time space network
Kepaptsoglou et. al.[19]	J. Transp. Eng.(2010)	Multi Depot-allocation bus to depot	Mixed integer-quadratic programming problem
Pepin et. al.[20]	J Sched (2009)	MD-EBSP	Heuristics
Wen et. al.[21]	Comput Oper Res (2016)	MD-(E)VSP (charging considered)	Adaptive large neighborhood search heuristic

Table 2.2: Overview of Studies on Electric Vehicle Routing and Scheduling Problems, Part 1

assimilated the heterogeneous fleet limitation. (6) is determined in a strong part by the sources and technical availability in the depots. (7) and (8) consider the limitation of work time of drivers and define feasible pairs of trips based on the time needed for a vehicle to travel from the end location of one trip to the start location of another trip, respectively. Finally, (9)-(11) are constraints related to the charger area of electric vehicles. Tables 2.4 and 2.5 demonstrate the presence of these constraints.

The Objective Functions presented in the Literature Review mostly consider the cost associated with some distance or time, charging infrastructure cost, and

Author	Journal (year)	Problem	Method Used
Wang et. al.[22]	Appl Soft Comput (2021)	MD-(E)VSP (connection network)	Column generation approach based on a genetic algorithm
Wu et. al.[23]	Transp Res Part B Methodol(2022)	MD-(E)VSP (pricing and peak)	Branch-and-price
Xu et. al.[24]	Energy (2023)	MD-EBSP(timetabling)	Lagrangian relaxation heuristic
Foda et. al.[25]	Energy (2023)	MD-EBSP (heterogeneous charging station network)	Surrogate model-based space mapping
He et. al.[26]	Transport Res Transport Environ (2023)	Charging scheduling for Battery Electric Buses (BEB)	Mixed-integer nonlinear programming(MINLP) horizon method
Gairola et. al.[27]	Transport Res Transport Environ (2023)	BEB	Robust optimization
Gkiotsalitis et. al.[5]	Eur J Oper Res (2023)	MD-(E)VSP(with time windows)	MINLP, exact optimization

Table 2.3: Overview of Studies on Electric Vehicle Routing and Scheduling Problems, Part 2

buying buses and the opening/closing of depots. To compare the objective function for each author is consider the following enumeration with cost related.

1. Deadhead cost: Pull-in and Pull out
2. Deadhead cost: Between trips
3. Vehicle cost: Variable
4. Vehicle cost: Fixed
5. Capital cost: New depots

Reference	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Prakash et. al.[7]	✓	✓	✓	✓							
Wang et. al.[4]	✓		✓		✓	✓	✓		✓	✓	
Mahadikar et. al.[8]		✓									
Eliiyi et. al.[9]	✓	✓	✓								
Narasimha et. al.[10]	✓	✓	✓	✓							
Haghani et. al.[11]	✓	✓	✓	✓							
Salhi et. al.[12]	✓	✓	✓	✓	✓	✓	✓				
Olariu et. al.[6]	✓	✓	✓	✓				✓			
Willoughby et. al.[13]	✓	✓	✓				✓				
Mancini et. al.[14]	✓	✓	✓	✓	✓						
Olsen et. al.[18]	✓	✓	✓	✓		✓		✓	✓		
Yao et. al.[15]	✓	✓	✓	✓	✓			✓	✓	✓	
Zhang et. al.[16]	✓	✓	✓	✓				✓	✓		
Cui et. al.[17]	✓			✓	✓				✓		
Pepin et. al.[20]	✓	✓	✓								
Wen et. al.[21]	✓	✓	✓	✓			✓	✓	✓		

Table 2.4: Constraints in the literature, Part 1

6. Capital cost: Close depots

7. Capital cost: Charging station infrastructure

Reference	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Wang et. al.[22]	✓	✓	✓	✓			✓	✓	✓		
Wu et. al.[23]	✓	✓	✓	✓				✓	✓		
Xu et. al.[24]	✓	✓	✓	✓					✓		
Foda et. al.[25]									✓	✓	
He et. al.[26]			✓	✓		✓		✓	✓	✓	✓
Gairola et. al.[27]	✓			✓					✓		✓
Gkiotsalitis et. al.[5]	✓	✓	✓	✓	✓			✓	✓	✓	✓
Kepaptoglou et. al.[19]		✓			✓	✓				✓	

Table 2.5: Constraints in the literature, Part 2

8. Capital cost: Buying electric buses

9. Vehicle cost: For charging type

From these characteristics, (1) and (2) are the deadhead costs, been the second about the waiting and reincorporation cost for second trips. (3) is about the distance relation for the driving activity, which can include multi-vehicle cases. (4) is the cost of activation of the trip in one vehicle, usually the driver's cost. (5) and (6) are the costs of the strategy of the depots available. (7) and (8) have a high relation to the necessity of having the infrastructure for the new buses in the strategy. The (9) objective function is for the divided consideration of the batteries. Table 2.6 includes the details of the objectives of the research.

Gerbaux et al.[28] use machine learning for solution the VSP considering only electric vehicles, with column generated schedules.

The Multi Depot Vehicle Scheduling Problem is an NP-hard problem [10]. Aggregated a heterogeneous fleet characteristic is a Multi-Fleet Vehicle Scheduling Problem is NP-hard because that can be reduced to a Vehicle Scheduling Problem, as suggested by Salhi et al.[12].

To address this problem, the following authors present various solution approaches. Olsen et al. [18] introduce a Mixed Fleet Electric Vehicle Scheduling

Reference	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Prakash et. al.[7]	✓								
Wang et. al.[4]	✓	✓		✓					✓
Mahadikar et. al. [8]	✓								
Eliiyi et. al.[9]	✓	✓	✓						
Narasimha et. al.[10]	✓		✓						
Haghani et. al.[11]	✓	✓	✓						
Salhi et. al.[12]			✓	✓					
Olariu et. al.[6]	✓	✓	✓	✓					
Willoughby et. al.[13]	✓	✓	✓			✓			
Mancini et. al.[14]	✓	✓	✓						
Olsen et. al. [18]	✓	✓	✓	✓					
Yao et. al.[15]	✓	✓	✓	✓			✓	✓	
Zhang et. al.[16]	✓	✓	✓	✓				✓	
Cui et. al.[17]				✓					
Pepin et. al.[20]	✓	✓	✓						
Wen et. al.[21]	✓	✓	✓						
Wang et. al.[22]	✓	✓	✓	✓					
Wu et. al.[23]	✓	✓	✓	✓					✓
Xu et. al.[24]	✓	✓	✓	✓					
Foda et. al.[25]	✓	✓	✓	✓			✓		
He et. al.[26]							✓	✓	✓
Gairola et. al.[27]				✓				✓	✓
Gkiotsalitis et. al.[5]	✓	✓		✓					✓
Kepaptsoglou et. al.[19]	✓	✓							

Table 2.6: Objective Functions in the Literature

Problem (MF-EVSP) as an extension of the traditional Vehicle Scheduling Problem (VSP), aiming to minimize operational costs. Thought a Time-Space network framework proposed by Kliewer et al. [29], elaborated a efficiency and real-world applicability. Their procedure starts in a mixed-integer linear program (MILP) for the VSP without range limitations, then incorporating driving range limitations through flow decomposition methods, and finally, the integration of charging procedures into vehicle rotations. Olsen et al. [18], Cui et al. [17] investigated about a mixed bus fleet problem. with a single depot. The both formulated a mixed-integer lineal model to optimize the Vehicle Scheduling Problem and recharging activities for electric vehicles, with constraints of restricted charging range.

Regarding to the multi-objective lineal programming model with mixed fleets, is founded the research by Ercan et al. [1] and Battaia et al. [30]. Ercan et al. [1] is focused by minimizing life cycle assessment impacts, while Battaia et al. [30] aimed to maximize the route-weighted total passenger capacity of electric buses.

Wang et al. [4] proposed a mixed-integer programming model for optimize the Multi-Depot-Electric Bus Scheduling Problem(MD-EBSP). This model is non linear due the interaction related to the battery variables and assignation to trip variables. The batteries system are one of the more complicated characteristics when is introduced the electric vehicles. Yao et al. [15] also present for the Multiple Vehicle Types Electric Vehicle Scheduling Problem (MVT-E-VSP) in the public transport relations between the level of battery, the decision of charging and the decision of assign a trip demonstrating the complexity of find solutions for this problems. Gairola et al. [27] follow a focus in the planing and strategy of the battery system included the charging sector, the relation between the both decisions are strongly related. They emphasized the strong relationship between these two decision areas, explaining how a smaller battery require a greater number of chargers and a higher charging frequency compared to a larger battery. Notably, their solution did not provide a mixed-integer linear programming (MILP) model.

The real-world complexity of the public transport transition unfolds in numerous steps and detailed descriptions. This work's primary contribution is the development of a Mixed-Integer Linear Model(MILP) capable of managing the expanding diversity of vehicles in these systems. This model accounts for the current trend of cities adopting multi-energy fleets, including the operational specificity of range-limited vehicles like BEVs.

The Problem Description is detail in the Section **??**. The development of a model for reach the features describes in the Section **??** are presented in the Section **??**. Eventually to generated a Mathematical Model, the Section 4 present the results of the programming application. The conclusion and Future work are describe in the Section 6.

Chapter 3

Problem Description and Mathematical Model

Considering the different solutions and interpretations of the public transport system in the Literature, specially to the inclusion of electric vehicles this chapter present an specific Problem and developed a Mathematical Model to address it. First, Section 3.1 present Mixed Fleet Electric Vehicle Problem details, including the explanation of the given information and assumptions to considerate for the mathematical formulation. Following this, Section 3.2 describes the model's evolution, starting from a foundational model from the literature review and progressively integrating new constraints and variables to create a Mixed-Integer Linear Programming (MILP) model tailored to the Problem Description's characteristics. The final model is then evaluated in Section 4 and Section 5, utilizing both randomly generated city data and a real-world application.

3.1 Problem Description

The constitution of the transport system for urban cities presents diverse type of vehicles about size and energy sources. Considering this context, Olsen et al. [18] introduced the Mixed Fleet-Electric Vehicle Scheduling Problem(MF-EVSP) as an extension of the traditional Vehicle Scheduling Problem(VSP). This problem integrate both electric and traditional vehicles-compressed natural gas(CNG) and diesel, addressing the charging scheduling complexities.

Even if the electrification of the transport system is growing, the actual and future cities will not easily operate with only electric vehicles. The transitions need time, improvement, and investment. The problem addressed by this document does not include the budget segment for vehicles, instead the focus is in the operational cost by type of vehicle. In this way, the mixed fleet approach includes diverse energy sources of the current transportation landscape- diesel, CNG, and electric vehicles.

A critical consideration when discussing electric vehicles is battery capacity, which affects both their application within the model and the associated costs. In essence, in current and future electric systems, the range of battery size is not homogeneous. The variety can significantly impact the operational decisions: vehicles with larger batteries are available of longer distances without recharging requirements, while smaller batteries need charging between trips through previous planning in charging stations and recharging times. As a result, for incorporating the batteries into the public system, their capacity has a significant influence on economic and logistical decisions. An important feature to add to the MF-VSP is the incorporation of non-identical sizes of batteries, measuring their effect on operational choices.

The primary objective of the MF-(E)VSP is equal to the traditional Vehicle Scheduling Problem. The task consists of assigning a timetable trip to a fleet of vehicles characterized by their attributes, such as energy sources and distance capacity. The problem selected doesn't consider the after or on procedure changes in the fleet through acquisition activities. Each trip is assigned to a specific vehicle, and the vehicle is related to a selected depot for starting and ending its loops. Each vehicle's rotation constant is from a set of feasible trips, including pull-in, pull-out, deadhead, and service trips, with fixed distances for each segment.

Furthermore, the efficiency of each vehicle is highly related to the distance capacity. For concept of this model does not consider the behavior of each driver. The State of Charge(SoC) of each battery electric vehicle has minimum and maximum levels, which are as follows in the travel and charging activities. Charging is only permitted at select depots, each equipped with a limited number of chargers operating at a uniform charging rate. All electric vehicles are assumed to be compatible with the existing charging infrastructure. In contrast, diesel and CNG vehicles are treated as having unlimited driving capacity or with non-time charging, and variations in passenger capacity are not addressed due to a lack of demand data. It is understated that the creation of the lines and their timetables in real cities is associated with investigations of demand. This problem considers the punctuality of the vehicles.

The compatibility of charging across multiple depots also depends on the actual distribution model and distances related to the different energy sources. Thus, utilizing an electric vehicle for a given trip involves considerations related not only to driving costs but also to minimum distance requirements and the availability of return depots.

3.2 Mathematical Formulations

For the definition of the model that integrates the characteristics outlined in the Problem Description (Section **??**), the proposed model by Yao et al. [15] serves as the foundation. The starting point is a model that incorporates features of electric vehicles and the task of assigning a scheduled timetable to a fleet of buses.

The following sections detail the modeling process, providing greater information about each specific features. Section 3.2.1 grant the model developed by Yao et al. [15], the basis model for the formulation that incorporate the characteristics proposed for the MF-(E)VSP. After this Section is generated a logical evolution formulated for defined a final model for study, this process include some features step by step into the models of the problem defined, the end is a model available for measure. For simplify the non-linear aspects of the initial model 3.2.1, initiating with the model in the Section 3.2.2 omitting certain charging features. For improve the model, in the Section 3.2.3 is introduce the temporal division for track battery and charging information. This case considerate a base for computational evaluation. The Section 3.2.4 considerate a larger number of periods to achieve minute-level detail. This case is the higher specific for a realistic battery and charger use, but could be to complicated for find solutions. For the incorporation of traditional vehicles, the model in the Section 3.2.5 present the multi fleet use, considering the constraints for electric vehicles proposed i the Section **??**. The temporal detail significative a complication with the programming measurement, for this reason is applied to a less detail cycle case of modeling at 3.2.6.

3.2.1 Model of Literature

For a base due the Literature Review is selected the model proposed by Yao et al. [15]. The model defined the trips $i, j \in S$ with S as the Set of trips. The Set S is indexed by the type of vehicle feasible $u \in U$, in result the Set S_u represent the conjunct of scheduled trips for a vehicle type u. Consequently $S = \bigcup_{u \in U} S_u$.

For the vehicle considerations, the Set K is the conjunct of Electric Buses(EBs), indexed by the type of vehicle $u \in U$ as K_u. This notation allows different vehicles characteristics into the Optimization Model. Been, k_u the vehicle by type u from the Set K_u of vehicles of this type. In essence, the Set $K = \bigcup_{u \in U} K_u$. Additionally, the depot q is part of the Set of depots Q and the charger p of the Set of Chargers P. The Table 3.1 present the variables and parameters of the Model. The equations (3.1) to (3.9) present the Function Objective and Constraints that are developed by the author.

While Yao et al. [15] formulated their objective function based on a yearly plan, this analysis, focusing on operational considerations, will only take into account the equations relevant to a short-term problem.

Parameters:	
D_u	the maximum driving range of the EB for vehicle type u, in km;
c_q^u	the capacity of depot q for vehicle type u
α	the discharging depth of EBs for all vehicles types;
θ_u	the recharging rate (i.e., the extended driving distance with the energy recharged per minute) of the EB for vehicle type u, in km/min;
t_p^u	the recharging duration of the EB for vehicle type u, in min;
e_i	end time of timetabled trip i, in min;
s_j	start time of timetabled trip j, in min;
t_{ij}	the deadheading distance between the destination of i to the origin of j, in min;
l_{iq}	deadheading distance between depot q and the origin of j, in km;
l_{qj}	deadheading distance between the destination of i and depot q, in km;
c_u^1	operating cost per unit deadheading distance of the EB for vehicle type u, in CNY/km;
c_u^2	operating cost per unit passenger-carrying distance of the EB for vehicle type u, in CNY/km;
l_{ij}	deadheading distance between the destination of i and the origin of j, in km;
l_i, l_j	driving distance timetabled trip i,j, in km;
Variables:	
Y_{ku}	0-1 variable indicating if EB k_u has been used within a day;
R_p	0-1 variable indicating if charger p has been used within a day;
Z_i^p	0-1 variable indicating of the EB is recharged by charger p after performing timetabled trip i;
$X_{k_u}^{ij}$	0-1 variable indicating if timetabled trips i and j are connected, and both performed by EB k_u;
$X_{k_u}^{qj}$	0-1 variable indicating if EB k_u performs timetabled trip j after going out of depot q;
$X_{k_u}^{iq}$	0-1 variable indicating if EB k_u goes into depot q after performing timetabled trip i;
E_i/E_j	extended driving distance with the residual energy at the end of i/j, in km;
$S_{k_u}^q$	0-1 variable indicating if EB k_u departs from depot q at the beginning;
$E_{k_u}^q$	0-1 variable indicating if EB k_u returns to depot q at the end of its schedule.

Table 3.1: Variables and Parameters of Yao et. al. [15] Model

1. **Objective Function**

$$min \quad Z = \sum_{u \in U} \sum_{k_u \in K_u} \sum_{i \in S_u} \sum_{j \in S_u} c_u l_{ij} X_{k_u}^{ij} \tag{3.1}$$

2. **Constraint: Limitation of charger use**

$$\sum_{p \in P} Z_i^p \leq 1, \quad \forall i \in S_u \tag{3.2}$$

3. **Constraint: Every timetabled must to be performed by one vehicle**

$$\sum_{u \in U} \sum_{k_u \in K_u} (\sum_{i \in S_u} X_{k_u}^{ij} + \sum_{q \in Q} X_{k_u}^{qj}) = 1, \quad \forall j \in S_u \text{ and } i \neq j \tag{3.3}$$

4. **Constraint: Every timetable must to be performed by one vehicle**

$$\sum_{u \in U} \sum_{k_u \in K_u} (\sum_{i \in S_u} X_{k_u}^{ij} + \sum_{q \in Q} X_{k_u}^{iq}) = 1, \quad \forall i \in S_u \text{ and } i \neq j \tag{3.4}$$

5. **Constraint: Connection between trips**

$$e_i + t_{ij} X_{k_u}^{ij} \leq s_j, \quad \forall i, j \in S_u, \forall k_u \in K_u \tag{3.5}$$

6. **Constraint: Minimum battery level**

$$E_i - l_{iq} \geq (1 - \alpha) D_u, \quad \forall i \in S_u, \forall u \in U \tag{3.6}$$

7. **Constraint: Recharging and residual energy**

$$E_j = \begin{cases} E_i - l_{iq} + \theta_u t_p^u - l_{qj} - l_j, \text{ if } Z_i^p = 1 \\ E_i - l_{ij} - l_j, \text{ if } Z_i^p = 0 \end{cases} \qquad \forall i, j \in S_u, \forall u \in U \text{ and } X_{k_u}^{ij} = 1 \tag{3.7}$$

8. **Constraint: The initial and end depot are the same for each vehicle**

$$S_{k_u}^q = E_{k_u}^q, \quad \forall k_u \in K_u, \forall q \in Q \tag{3.8}$$

9. **Constraint: Capacity of the depot**

$$\sum_{k_u \in K_u} S_{k_u}^q = \sum_{k_u \in K_u} E_{k_u}^q \leq C_q^u, \quad \forall q \in Q, \forall u \in U \tag{3.9}$$

The model incorporates constraints related to the electric vehicle application. Constraint (3.2), ensure the non multiple use of charger by a battery electric vehicle(BEV). Constraints (3.3) and (3.4) guarantee that each timetabled trip i or

j is exclusively assign to an unique BEV given the type. The correct link between trips is realized by the constraint (3.3) connecting a trip j to a preceding trip, possible trip i or from a depot q. Similarly, constraint (3.4) related a trip i into a sequence of trip with a following trip j or a return to depot. The association between two trips are secure by constraint (3.5). About the battery management, constraint (3.6) guarantees that the level of State of Charge(SoC) is higher than the minimum defined, while constraint (3.7) tracks the residual charge at the end of a trip. For operational definitions the constraint (3.8) ensure that all the vehicles return to their assigned depot after completing the schedule for recharging and maintenance activities. This constraint is detailed by the each vehicle. Lastly, constraint (3.9) check that the number of vehicles by a type are less or equal to the capacity of storage for them.

The model proposed by Yao et al. [15], the change in the SoC is related to the variables $X_{k_u}^{ij}$ and Z_i^p by constraint (3.2). Both variables linked to a positional information, indicating whether the vehicle is available for use the a charger. Subsequent to introducing their model, Yao et al. [15] proceeded to apply a genetic algorithm for the main procedural flow, complemented by an additional algorithm for obtaining feasible schedules of EBs.

3.2.2 E-VSP with charging paths

Based on Yao at et. [15] model is proposed a formulation that assimilated the charging state change thought the taking paths decision. In this way, there is not a Z_i^p, instead is used a $X_{k_u}^{ij}$ with connections between $i \in D$ and $j \in F$, been F a set of available chargers. The optimal function rest the same.

For aggregate the chargers thought the decision variable $X_{k_u}^{ij}$ is applied a serial of constraints about the charging and battery limitations.

The presented formulation integrate a flow of BEVs, but without the time consideration, charging events are not available to follow on detail. The constraint **??** brings the limitations that should follow the charging and discharging actions. But as the equation brings all the events during the total period for the existing charging.

1. Objective Function

$$min \quad Z = \sum_{u \in U} \sum_{k_u \in K_u} \sum_{i \in S_u \cup Q} \sum_{j \in S_u \cup Q} c_u l_{ij} X_{k_u}^{ij} \tag{3.10}$$

2. Constraint: Every timetabled trip can only be performed by one vehicle

$$\sum_{u \in U} \sum_{k_u \in K_u} \left(\sum_{i \in S_u} X_{k_u}^{ij} + \sum_{q \in Q} X_{k_u}^{qj}\right) = 1, \quad \forall j \in S_u \text{ and } i \neq j \tag{3.11}$$

3. Constraint:Every timetabled trip can only be performed by one vehicle

$$\sum_{u\in U}\sum_{k_u\in K_u}(\sum_{i\in S_u} X^{ij}_{k_u} + \sum_{q\in Q} X^{iq}_{k_u}) = 1, \quad \forall i \in S_u \text{ and } i \neq j \tag{3.12}$$

4. Constraint: Connection between trips

$$e_i + t_{ij}X^{ij}_{k_u} \leq s_j, \quad \forall i, j \in S_u, \forall k_u \in K_u \tag{3.13}$$

5. Constraints: Flow by the electric battery

$$\alpha D_u \geq \sum_{i\in Q, j\in P} X^{ij}_{k_u}\theta_u - \sum_{(i,j)\in S_u\cup Q, i\neq j} X^{ij}_{k_u} l_{ij} \geq 0, \quad \forall k_u \in K_u, \forall u \in U \tag{3.14}$$

6. Constraint: Limitation of energy to charge

$$\sum_{\{i\in Q, j\in P\}} X^{ij}_{k_u}\theta_u \leq \beta\alpha D_u, \quad \forall k_u \in K_u, \forall u \in U \tag{3.15}$$

7. Constraint: In-out of charging station

$$X^{ij}_{k_u} = X^{ji}_{k_u}, \quad \forall i \in Q, \forall j \in P \tag{3.16}$$

8. Constraint: Initial and end depot are the same for a given vehicle

$$S^q_{k_u} = E^q_{k_u}, \quad \forall k_u \in K_u, \forall q \in Q \tag{3.17}$$

9. Constraint: Depot capacity

$$\sum_{k_u\in K_u} S^q_{k_u} = \sum_{k_u\in K_u} E^q_{k_u} \leq C^u_q, \quad \forall q \in Q, \forall u \in U \tag{3.18}$$

The present model defines the constraint 3.11 and 3.12 to ensure that every trip is assigned to a vehicle. Constraint 3.13 relates previous and later trips as the model before. Following the SoC changes at each vehicle delimitates the total flow through the constraint 3.14, been α is the percentage available to use of the total battery D_u. Searching to delimitate the total charge that can be performed a charging station is applied the constraint 3.15. As is added a trip-charging case, the constraint 3.16 verifies that if a charging event also returns to the depot. Constraint 3.17 determines that the same depot of start is the end point for the vehicle. 3.18 presents the depot capacity at the start and end of the day.

For this model, the control of the battery and the charging activities is free. In this case, for not following the availability of a charger at a time, their use doesn't follow a limit in number or charging capacity.

3.2.3 E-VSP with periods

To determine the changes in the State of Charge (SoC) resulting from charger usage and travel, this approach employs discrete time periods, thereby avoiding the need to consider every hour or minute. The proposed methodology involves the division of the day into 3, aligned with anticipated demand patterns. In this context, the energy level of a vehicle at the end of the final period, $r = 3$, is specifically tracked. In the same way, $E_{0k_u} = D_u$ indicate that at the beginning of the day the SoC of the vehicle k_u is equal to the complete charge battery(100%).

For the variable $X^{ij}_{rk_u}$, representation the decision of the trip i to j for a vehicle k_u in a defined period r, the level SoC of the battery at the start of a the period is measured. Consequently, the amount of energy available for charging during the same period is determinate.

For a given scenario, the charging action is delimited to a unique charging event within a single period. The objective function, defined in equation (3.19), considers the sum of total cost without passengers during the periods R, based on the variable decisions $X^{ij}_{rk_u}$.

1. Objective Function

$$min \quad Z = \sum_{u\in U}\sum_{k_u\in K_u}\sum_{r\in R}\sum_{i\in S_u\cup Q}\sum_{j\in S_u\cup Q} c_u l_{ij} X^{ij}_{rk_u} \tag{3.19}$$

2. Constraint: One trip per vehicle, flow-in

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{r\in R}(\sum_{i\in S_u} X^{ij}_{rk_u} + \sum_{q\in Q} X^{qj}_{rk_u}) = 1, \quad \forall j \in S_u \text{ and } i \neq j \tag{3.20}$$

3.Constraint: One trip per vehicle, flow-out

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{r\in R}(\sum_{i\in S_u} X^{ij}_{rk_u} + \sum_{q\in Q} X^{iq}_{rk_u}) = 1, \quad \forall i \in S_u \text{ and } i \neq j \tag{3.21}$$

4. Constraint: Connection between trips

$$e_i + t_{ij} X^{ij}_{rk_u} + \leq s_j, \quad \forall i, j \in S_u, \forall k_u \in K_u \tag{3.22}$$

5. Constraint: Initial and end depot are the same for a given vehicle

$$S^q_{k_u} = E^q_{k_u}, \quad \forall k_u \in K_u, \forall q \in Q \tag{3.23}$$

6. Constraint: Depot capacity

$$\sum_{k_u\in K_u} S^q_{k_u} = \sum_{k_u\in K_u} E^q_{k_u} \leq C^u_q, \quad \forall q \in Q, \forall u \in U \tag{3.24}$$

7. Constraint: Initial energy available in the period for a given vehicle

$$E_{r+1k_u} = E_{rk_u} + \sum_{i\in Q, j\in P} X^{ij}_{rk_u}\theta_u - \sum_{(i,j)\in S_u\cup Q, i\neq j} X^{ij}_{rk_u} l_{ij}, \quad \forall r\in R, \forall u\in U, \forall k_u\in K_u \tag{3.25}$$

8. Constraint: Available energy for charge during a period for a given vehicle

$$\sum_{i\in Q, j\in P} X^{ij}_{r+1k_u}\theta_u \leq D_u - E_{rk_u}, \quad \forall r\in R, \forall u\in U, \forall k_u\in K_u \tag{3.26}$$

9. Constraint: Energy availability of charger

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{j\in P} X^{ij}_{rk_u} \leq CC_f, \quad \forall r\in R, \forall i\in Q \tag{3.27}$$

For this model, constraints 3.20 and 3.21 present the assignment of a trip to a only vehicle. Constraint 3.22 define the connection between trips. As [15], constraint 3.23 ensures that the vehicle starts and ends at the same depot. Additionally, constraint 3.24 limits the number of vehicles available to stay at the depot. To integrate the period characteristic is follow the energy in each vehicle k_u at period r, E_{rk_u} is present at constraint3.25 including the battery flow. The information of parallel charging is not available for the extensive of the period time, constraint 3.27 is add for delimited the energy for charge during the period.

3.2.4 E-VSP with minute time

Following the previous Models in the Section 3.2.2 and Section 3.2.3 with the temporal considerations. The present model includes time track periods for battery level and use of chargers. For this model, the periods reflect the minute-by-minute information. This type of use availability to an exact measure of battery level by vehicle, parallel use of chargers without a period delimited.

1. Objective Function

$$min \quad Z = \sum_{r\in R}\sum_{u\in U}\sum_{k_u\in K_u}\sum_{i\in S_u\cup Q}\sum_{j\in S_u\cup Q} c_u l_{ij} X^{ij}_{rk_u} \tag{3.28}$$

2. Constraint: Each Trip is run by just one vehicle, flow-in

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{r\in R}\Big(\sum_{j\in S_u, i\neq j} X^{ij}_{rk_u} + \sum_{q\in Q} X^{qj}_{rk_u}\Big) = 1, \quad \forall j\in S_u \tag{3.29}$$

3. **Constraint: Each Trip is run by just one vehicle, flow-out**

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{r\in R}(\sum_{i\in S_u,i\neq j} X^{ij}_{rk_u} + \sum_{q\in Q} X^{iq}_{rk_u}) = 1, \quad \forall i \in S_u \tag{3.30}$$

4. **Constraint: Connection between trips**

$$e_i + t_{ij}X^{ij}_{rk_u} \leq s_j, \quad \forall i,j \in S_u, \forall k_u \in K_u \tag{3.31}$$

5. **Constraint: Initial and end depot are the same for a given vehicle**

$$S^q_{k_u} = E^q_{k_u}, \quad \forall u \in U, \forall k_u \in K_u, \forall q \in Q \tag{3.32}$$

6. **Constraint: Depot capacity**

$$\sum_{k_u\in K_u} S^q_{k_u} = \sum_{k_u\in K_u} E^q_{k_u} \leq C^u_q, \quad \forall q \in Q, \forall u \in U \tag{3.33}$$

7. **Constraint: Battery energy**

$$E_{r+1k_u} = E_{rk_u} + \sum_{i\in Q,j\in P} X^{ij}_{rk_u}\theta_u - \sum_{(i,j)\in S_u\cup Q,i\neq j} X^{ij}_{rk_u} l_{ij}, \quad \forall r \in R, \forall u \in U, \forall k_u \in K_u \tag{3.34}$$

8. **Constraint: Available energy for charge**

$$\sum_{i\in Q,j\in P} X^{ij}_{r+1k_u}\theta_u \leq D_u - E_{rk_u}, \quad \forall r \in R, \forall u \in U, \forall k_u \in K_u \tag{3.35}$$

9. **Constraint: Minimum level of battery**

$$E_{rk_u} \geq (1-\alpha)D_u, \quad \forall r \in R, \forall u \in U, \forall k_u \in K_u \tag{3.36}$$

10. **Constraint: Not parallel use in charger**

$$\sum_{u\in U}\sum_{k_u\in K_u}\sum_{q\in Q} X^{ij}_{rk_u} \leq 1, \quad \forall r \in R, \forall j \in P \tag{3.37}$$

This model offers a higher level of temporal specification. As in previous models, its objective function minimizes the cost of empty vehicle travel (distance without passengers), as shown in Constraint 3.28. Initially, Constraints 3.29 and 3.30 ensure each trip is assigned to a unique vehicle. Constraint 3.31 links consecutive trips with time restrictions. To guarantee that a vehicle's starting depot is the same as its ending depot, constraint 3.32 is added. Constraint 3.33 limits the number of vehicles that can start or end at a depot due to capacity. Regarding the battery level during a session, Constraint 3.34 models the energy flow between use and charging. Constraint 3.36 ensures the State of Charge (SoC) remains above its minimum level. Finally, Constraint 3.37 prevents a charger from being used by two or more vehicles simultaneously at a given time r.

3.2.5 Mixed Fleet-EVSP

The motivation is the use of more than one type of energy source, driven by the actual cities' compositions. For this reason, the type of vehicle is divided into traditional and electric vehicles. In this case, traditional vehicles don't follow a limitation on distance capacity during the session. However, traditional vehicles should start and end in the same depot, among other basic constraints.

In this model, is define the set of Electric Vehicles as EV and the set of Traditional Vehicles as TV. The complete set of vehicles, denoted by K, is the union of these two sets: $K = EV \cup TV$.

1. **Objective Function: Minimization of distance**

$$min \quad Z = \sum_{r \in R} \sum_{u \in U} \sum_{k_u \in K_u} \sum_{i \in S_u \cup Q} \sum_{j \in S_u \cup Q} c_u l_{ij} x_{rk_u}^{ij} \tag{3.38}$$

2. **Constraint: Each Trip is run by just one vehicle, flow-in**

$$\sum_{u \in U} \sum_{k_u \in K_u} \sum_{r \in R} (\sum_{i \in S_u, i \neq j} X_{rk_u}^{ij} + \sum_{q \in Q} X_{rk_u}^{qj}) = 1, \quad \forall j \in S_u \tag{3.39}$$

3. **Constraint: Each Trip is run by just one vehicle, flow-out**

$$\sum_{u \in U} \sum_{k_u \in K_u} \sum_{r \in R} (\sum_{j \in S_u, i \neq j} X_{rk_u}^{ij} + \sum_{q \in Q} X_{rk_u}^{iq}) = 1, \quad \forall i \in S_u \tag{3.40}$$

4. **Constraint: Connection between trips**

$$e_i + t_{ij} X_{rk_u}^{ij} \leq s_j, \quad \forall r \in R, \forall i, j \in S_u, \forall u \in U, \forall k_u \in K_u \tag{3.41}$$

5. **Constraint: Depot assignation**

$$S_{k_u}^q = E_{k_u}^q, \quad \forall u \in U, \forall k_u \in K_u, \forall q \in Q \tag{3.42}$$

6. **Depot Capacity**

$$\sum_{k_u \in K_u} S_{k_u}^q = \sum_{k_u \in K_u} E_{k_u}^q \leq C_q^u, \quad \forall q \in Q, \forall u \in U \tag{3.43}$$

7. **Depot Capacity for Electric Vehicles**

$$\sum_{u \in EV} \sum_{k_u \in K_u} S_{k_u}^q = \sum_{u \in EV} \sum_{k_u \in K_u} E_{k_u}^q \leq \sum_{u \in EV} C_q^u, \quad \forall q \in Q \tag{3.44}$$

8. **Depot Capacity for Traditional Vehicles**

$$\sum_{u \in TV} \sum_{k_u \in K_u} S_{k_u}^q = \sum_{u \in TV} \sum_{k_u \in K_u} E_{k_u}^q \leq \sum_{u \in TV} C_q^u, \quad \forall q \in Q \tag{3.45}$$

9. Constraint: Battery energy

$$E_{r+1k_u} = E_{rk_u} + \sum_{i \in Q, j \in P} X^{ij}_{rk_u} \theta_u - \sum_{(i,j) \in S_u \cup Q} X^{ij}_{rk_u} l_{ij}, \quad \forall r \in R, \forall u \in EV, \forall k_u \in K_u \tag{3.46}$$

10. Constraint: Available energy for charge

$$\sum_{i \in Q, j \in P} X^{ij}_{r+1k_u} \theta_u \leq D_u - E_{rk_u}, \quad \forall r \in R, \forall u \in EV, \forall k_u \in K_u \tag{3.47}$$

11. Constraint: Minimum level of battery

$$E_{rk_u} \geq (1 - \alpha) D_u, \quad \forall r \in R, \forall u \in EV, \forall k_u \in K_u \tag{3.48}$$

12. Constraint: One charge at time

$$\sum_{u \in EV} \sum_{k_u \in K_u} \sum_{q \in Q} X^{qj}_{rk_u} = 1, \quad \forall r \in R, \forall j \in P \tag{3.49}$$

The objective function of the Model is defined in the equation 3.38, which aims to minimize the total distance cost made by vehicles. To ensure the realization of trips are the constraint 3.39 and constraint 3.40. The connection between trips is related to the constraint 3.41. The charging and depot stay case are between the trips. Constraint 3.43 defines the capacity of vehicles by type. While constraint 3.44 and constraint 3.45 delimit the number of available vehicles for rest in the depot by energy source. Constraint 3.46 determines the battery level at time $r + 1$, considering the flow during the previous periods. To the maximum charge, constraint3.47 ensures the energy available for charge into the battery in the period. To verify the minimum level of SoC, constraint 3.48 is used. Finally, constraint 3.49 ensures that during the use of a charger, only one vehicle is related to the action.

Nerveless, the higher level of detail into the temporal use is related to an intensive use of resource for find a solution. Prior work by Yao et al. [15] worked this through employing and initial information algorithm and a supplementary tool for find feasible solutions. Conversely, Olsen et al. [18] adopted a phased approach due the complexity of the problem. The procedure aims to find through divisions, solutions. For this reason, is proposed the use of cycles, defined by vehicles with a structure for less detail but without leaving some feature developed into this point.

3.2.6 MF-EVSP by Cycle

Following the time and space information is one of the challenges for understand how the vehicles and their charge develop their days of service. As was proposed the use of periods of times as tools significative a high weight of work for computational sources. Its define the use of Cycles, as a own defined period or conjunct of trips allows without charging actions between. During this route the vehicle accomplish a time-feasible trips. This sections of time are related in between for avoid that a vehicle assignation distribute the trips with same segments of time or without considering the time of charging used.

The velocity during passenger service periods is a predetermined value (v). The charging conversion time, denoted as t_c, is determined by the specific characteristics of the vehicle and charger. To account for charging as an equivalent distance, a decision variable w_{rk_e} is introduced. This variable represents the amount of kilometers gained from charging at the start of period $r \in R$ for vehicle $k_e \in K_e$

The concept of using Cycles aims to identify critical points where a vehicle's operation might necessitate charging. For instance, a vehicle's autonomy, defined by its battery capacity, allows for strategic optimization of energy use. By minimizing wasted energy during deadhead operations within a cycle, the goal is to maximize accomplished tasks before charging becomes essential. The optimal charge level for a vehicle should, therefore, depend on its subsequent trips. This means that if a vehicle is not scheduled for use for several hours, immediate charging is unnecessary. This approach currently focuses solely on battery usage and does not include a charging schedule, which would be handled by a separate algorithm.

This model seeks to minimize the temporal size of operations. However, as noted, it doesn't create a charging schedule. It does, however, assume that a charger is available at the selected depot.

Objective Function

$$Z = \sum_{u \in U} \sum_{k_u \in K_u} \Big(\sum_{i,j \in S, i \neq j} X_{ij}^{rk_u} c_u l_i + \sum_{q \in Q} \sum_{i \in S} X_{qi}^{rk_u} c_u l_{qi} + \sum_{q \in Q} \sum_{i \in S} X_{iq}^{rk_u} c_u l_{iq} \Big) \tag{3.50}$$

Constraint 1: Each trip, flow in

$$\sum_{r \in R} \sum_{k_u \in K_u} \Big(\sum_{i \in S, i \neq j} X_{ij}^{rk_u} + \sum_{q \in Q} X_{qj}^{rk_u} \Big) = 1, \quad \forall j \in S \tag{3.51}$$

Constraint 2: Each trip, flow out

$$\sum_{r \in R} \sum_{k_u \in K_u} \Big(\sum_{j \in S, i \neq j} X_{ij}^{r} k_u + \sum_{q \in Q} X_{iq}^{rk_u} \Big) = 1, \quad \forall i \in S \tag{3.52}$$

Constraint 3: Connection between trips

$$E_i + X_{ij}^{rk_u} t_{ij} \leq S_i, \quad \forall i, j \in S, with \quad i \neq j, if \quad S_i > E_i \tag{3.53}$$

Constraint 4: Depot Assignation

$$S_{k_u}^{q} = E_{k_u}^{q}, \quad \forall q \in Q, \forall k_u \in K_u \tag{3.54}$$

Constraint 5: Beginning of the Cycle

$$X_{qi}^{rk_u} \leq S_{k_u}^q, \quad r \in R, \forall q \in Q, \forall k_u \in K_u, \forall i \in S \tag{3.55}$$

Constraint 6: Final of the Cycle

$$E_{k_u}^q \leq \sum_{r \in R} \sum_{i \in S} X_{iq}^r k_u, \quad q \in Q, \forall k_u \in K_u \tag{3.56}$$

Constraint 7: Unique depot for each vehicle

$$\sum_{q \in Q} S_{k_u}^q = 1, \forall k_u \in K_u \tag{3.57}$$

Constraint 8: Flow between begging and ending

$$\sum_{i \in S} X_{qi}^{rk_u} = \sum_{i \in S} X_{iq}^{rk_u}, \quad \forall q \in Q, \forall k_u \in K_u \tag{3.58}$$

Constraint 9: Depot General Capacity

$$\sum_{k_u \in K_u} S_{k_u}^q = \sum_{k_u \in K_u} E_{k_u}^q \leq C_q^u, \quad \forall q \in Q \tag{3.59}$$

Constraint 10: Initial Battery Energy

$$\begin{aligned} SoC_{rk_u} = {} & SoC_{(r-1)k_u} + w_{rk_u} \\ & - \sum_{i,j \in S, i \neq j} X_{ij}^{(r-1)k_u}(l_{ij} + l_j) - \sum_{i \in S} \sum_{q \in Q} X_{qi}^{(r-1)k_u}(l_{qi} + l_i) \\ & - \sum_{q \in Q} \sum_{i \in S} X_{iq}^{(r-1)k_u} l_{iq}, \quad \forall r \in R - \{0\}, \forall k_u \in K_u \end{aligned} \tag{3.60}$$

Constraint 11: Available Energy for charge

$$w_{rk_u} \leq D_u - SoC_{(r-1)k}, \quad \forall r \in R - 0, \forall k_u \in K_u \tag{3.61}$$

Constraint 12: Minimum level of charge

$$0 \leq SoC_{rk_u}, \quad \forall r \in R, \forall k_u \in K_u \tag{3.62}$$

Constraint 13: Only one charger use for each cycle ended

$$\sum_{p \in P} \sum_{q \in Q} X_{qp}^{rk_u} \leq 1 \tag{3.63}$$

Constraint 14: Flow of nodes

$$\sum_{j\in S, i\neq j} X_{ji}^{rk_u} + \sum_{q\in Q} X_{qi}^{rk_u} = \sum_{j\in S, i\neq j} X_{ij}^{rk_u} + \sum_{q\in Q} X_{iq}^{rk_u}, \quad \forall r\in R, \forall i\in S, \forall k_u\in K_u \tag{3.64}$$

Constraint 15: Cycle starting time

$$\begin{aligned}\sum_{q\in Q}\sum_{i\in S} X_{qi}^{rk_u} s_i \leq \sum_{j\in S}\Bigg(&\sum_{i\in S, i\neq j} X_{ij}^{rk_u}\left(l_i\left(v\right)+t_{ij}\right)\\ &+\sum_{q\in Q} X_{qj}^{rk_u}\left(l_i\left(v\right)+s_j\right)\Bigg), \quad \forall r\in R, \forall k_u\in K_u\end{aligned} \tag{3.65}$$

Constraint 16: Cycle ending time

$$\sum_{j\in S}\Big(\sum_{i\in S, i\neq j} X_{ij}^{rk_u}(l_i v + t_{ij}) + \sum_{q\in Q} X_{qj}^{rk_u}(l_i v + s_j)\Big) \leq \sum_{q\in Q}\sum_{i\in S} X_{iq}^{rk_u} e_i \tag{3.66}$$

Constraint 17: Cycle relation time

$$\begin{aligned}M\left(1-\sum_{i\in S} X_{qi}^{rk_u}\right) + \sum_{i\in S} X_{qi}^{rk_u} s_i \geq \sum_{i\in S} X_{iq}^{fk_u} e_i + \sum_{p\in P} X_{qp}^{fk_u} w_{rk_u} t_c,&\\ \text{if } r > f, \quad \forall r\in R\setminus\{0\}, \forall f\in R, \forall q\in Q, \forall k_u\in K_u&\end{aligned} \tag{3.67}$$

Constraint 18: Charge relation

$$\sum_{p\in P}\sum_{q\in Q} X_{qp} D_u \geq w_{rk_u}, \quad \forall r\in R, \forall k_u\in K_u \tag{3.68}$$

Constraint 19: Limit distance per Cycle

$$\sum_{q\in Q}\sum_{i\in S} X_{qi}^{rk_u}(l_{qi}+l_i) + \sum_{i,j\in S, i\neq j} X_{ij}^{rk_u}(l_{ij}+l_j) + \sum_{i\in S}\sum_{q\in Q} X_{iq}^{rk_u} \leq D_u, \forall k_u\in K_u, \forall u\in EV \tag{3.69}$$

The objective function include the cost of deadhead kilometers given the decisions of buses assignation thought the 3.50. For accomplish all the trips of the journey the constraints 3.51 and constraint 3.52 ensure the flow thought trip points. Constraint 3.53 guarantee the temporal feasibility between the trips driven by a vehicle. For don't exceed the maximum available storage the constraint 3.59 limits the number of vehicles for a depot.

For the case of Cycle, the constraint 3.55 the starting from a depot of the a vehicle is connected to the initial assignation bus to depot. In this way, if is decide to start at a depot q to a trip i, the information of selection of the depot is taking into account. As the beginning, the cycle is closed thought the constraint 3.66.

For following the level of battery the constraint 3.60 related between the cycles and count the consume and the charging for made before start the cycle. The initial charge is assume complete. The energy that can be charge in the final of a cycle for start the next one is defined by the constraint 3.61. As the the state of charge is always equal or more than the minimal, the constraint 3.62 enforce the non-negativity. For define a non double charge or distributed charge, the constraint 3.63 define the use of only one charger when is required. The initial model developed by Yao et al. [15] with pre generated trips don't ensure the chain flow, for aggregated this feature the constraint 3.64 check the flow into and out the node. All the trips feasible for a vehicle should be with a starting time trip higher than the moment of start plus the time for arrive to the starting point of the trip, as is suggest by 3.65. At the same way, for return into the depot should be considerate the time of driving between trips, the trips and return, include in the constraint 3.66. For relate cycles the constraint 3.67 define the temporal affirmation for don't parallel driving cases. Finally, constraint 3.69 limit the available driving distance of a vehicle during a cycle.

Unlike models found in the literature, the proposed model does not rely on non-linear constraints. Furthermore, the definition of time-space variables does not necessitate an excessively high number of definitions, as is common with minute-by-minute tracking models. The cycle-based approach allows for the selection of trips based on an initial battery level, with the assigned depot remaining consistent for a vehicle across all cycles. Before starting a new cycle, charging is possible, and this decision updates the battery level for that cycle. For any cycle (r ¿ 0), the earliest possible start time for its trips is determined by the end time of the previous cycle at the depot and any charging time utilized. There is no enforced obligation to start from cycle (r=0). It is expected that due to the non-parallel nature of charging activities and cycle-specific limitations, the model will distribute charger usage across cycles, though this distribution is not strictly tied to real-time events.

The benefits derived from the application of cycles include the vehicle-specific definition of charging requirements and the accurate temporal connection between trips within the same cycle and across different cycles. This implies that the model, through its constraints, handles trip assignments without relying on a pre-processed structure. The primary disadvantage of this model, however, is the unconstrained simultaneous use of chargers by multiple vehicles during the same period.

Chapter 4

Model Implementation and Experimental Setup

The mathematical model selected for the study of a program application is the MF-(E)VSP by Cycle, given the resource uses. The notation, objective function and constraints available in the Section 3.2.1 and 3.2.6. The implementation is in the program language **Python 3.11**. The libraries used are **Pyomo**, for optimization model definitions, the solver **Gurobi**, and **Random** for generated instances. All the computational experiments were measured using a **Apple M1 machine with 8 GB of memory**. This section starts with the description of the parameter values, sets, and variables. Then, the test case generation with a general information. Subsequently, the results of the implementation with the selected cases are presented. The complete code developed is provided in the Appendix A.

4.1 General Parameters and Assumptions

For the experiments is considered a variety of electric vehicles and only a general type of non-traditional vehicle is considered. Regarding to the energy pricing, the study considers a single price for the traditional vehicle and a related vehicle price for electric vehicles due to their consumption and conversion to kilometers. In all the cases, the energy cost of diesel 1.323 EUR/l is higher than the electricity0.216 EUR/kWh. The prices are considered by public data of GTT[31].

The average speed for deadhead(non-passenger) kilometers is fixed to 20 km/hr. Typically, the traditional vehicles exhibit a long autonomy, for the studies are defined as 210 km, with a consumption of 52 l/100km. The cost related is 0.69 EUR/km for this vehicle type. The specific operational limits and parameters used for generating the test cases are comprehensively detailed in Appendix A.3.

Model	Battery (kWh)	Consumption (Wh/100km)	Charge Time 1 (6.6 kW)	Charge Time 2 (80 kW)	# Vehicles
Cacciamali Elfo	67	95	10.15 h	N/A	17
BYD K7	165	95	N/A	2.07 h	8
BYD K9 (1)	324	104	49 h	4.05 h	50
BYD K9 (2)	348	91	52.7 h	4.35 h	20

Table 4.1: Characteristics of GTT Electric Vehicles [31] before 2025.

Operational Costs for EVs: Two specific cost cases were developed for these EV models, based on their energy consumption rates:

- 0.207,2 EUR/km for vehicles consuming 95 Wh/100km
- 0.224,6 EUR/km for those consuming 104 Wh/100km

The cost are based in the 2024 contract define in the public documents by GTT[31].

Usable EV Autonomy: Segments of energy available for use considering a the battery heath and operational security. Given this, is considered the 60% of the total battery characteristic for each vehicle. As a result, the representation of SoC is between the 20% and the 80% of the original battery D_u. This measure is transcript to kilometers for easy use in the model.

4.2 Test Case Generation and Computational Limits

To measure the model's performance, **20 distinct city scenarios** were generated. Each city is characterized by a few depots, a size of timetabled and a fleet available for use, among other details. A maximum solution time is defined as **5 minutes, 300 seconds** for each optimization run.

The following tables present the essential details for the model's implementation. Table 4.2 contains the parameters and set descriptions. While Table 4.3 values are considered by each case applied, the details of results are presented in the next subsections. Finally, the Table 4.4 summarizes the objective function values and time incurred for each case. These results will be discussed later.

4.3 Computational Results and Scenario Analysis

Given the parameter's values, the following sections describe four conjuncts of the test realized. The sections are divided into general assumptions generated for study

Symbol	**Description**
Sets:	
R	Set of available cycles for the EVs
S	Set of trips
Q	Set of Depots
K	Set of general vehicles
K_e	Set of Electric Vehicles
K_t	Set of Traditional Vehicles
U	Set of vehicle types
Parameters:	
C_q	Capacity of depot q
s_i	Start time of trip i [min]
e_i	End time of trip i [min]
l_{ij}	Deadhead distance between endpoint of trip i and start point of trip j, $i, j \in S$[km]
l_{qi}	Deadhead distance between depot q and start point of trip i, $q \in Q, i \in S$[km]
l_{iq}	Deadhead distance between endpoint of trip i and depot q, $i \in S, q \in Q$[km]
t_{ij}	Deadhead travel time between endpoint of trip i and start point of trip j [min]
C_u	Price per kilometer by vehicle type $u \in U$[€/km]
l_i	Distance of trip $i \in S$[km]
D_u	Usable battery capacity (autonomy) by vehicle type u[km]

Table 4.2: Sets and Parameters Descriptions

the results of the model. A general observation across the cases consists of the comparison between the use of traditional vehicles, with higher operational costs, and the use of electric vehicles, which considers the distance to the chargers. The set of cities only brings charging services to depots. For this reason, a charging action is found a related to the distances between the trip area and the depots, compared to the cost of diesel vehicles per kilometers a fundamental point for the model.

City	#S	#Q	K	K_e	K_t
C1	50	2	10	6	4
C2	64	2	7	4	3
C3	40	2	7	4	3
C4	55	2	7	4	3
C5	48	2	7	4	3
C6	70	2	7	4	3
C7	72	2	4	3	1
C8	110	2	6	3	3
C9	110	2	7	4	3
C10	110	2	6	4	2
C11	130	2	8	5	3
C12	140	3	8	5	3
C13	160	3	8	5	3
C14	160	3	8	5	3
C15	170	3	8	5	3
C16	110	3	8	5	3
C17	120	3	8	5	3
C18	130	3	8	5	3
C19	140	3	8	5	3
C20	150	3	8	5	3

Table 4.3: Set Configurations by City Case

4.3.1 Baseline Scenarios (Cities 1-5: No Charging Incentive)

For these first cases, the cities {1,2,3,4,5} demonstrated the low charging activities for most of the cases. Except for the generated city C4, this contains one case of a huge use of charging battery, possibly explained by the random data, as is graphic in the Figure 4.2 of the Distribution of source in cities 1 to 5. In the case of city C1, the level of use of electric vehicles, visualized in the Figure 4.1 with Charging decisions for cities 1 to 5, is considered due to the higher battery capacity in comparison to other cases. In the same way, the Figure ensures a lower use of electric vehicles, with a higher use of traditional vehicles for the city C2, which is related to the lower battery capacity of the fleet and longer distances of trips. For the following cases, C3 and C4, the use of both numbers of vehicles of each type with different capacities a higher use of electric vehicles in comparative to traditional vehicles. The cases present different capacities and numbers of trips. For the city C5, the presence of charger use is incremented, their fleet is equal to C4, but with less trip numbers is resulting in a similar use of both vehicle type sources.

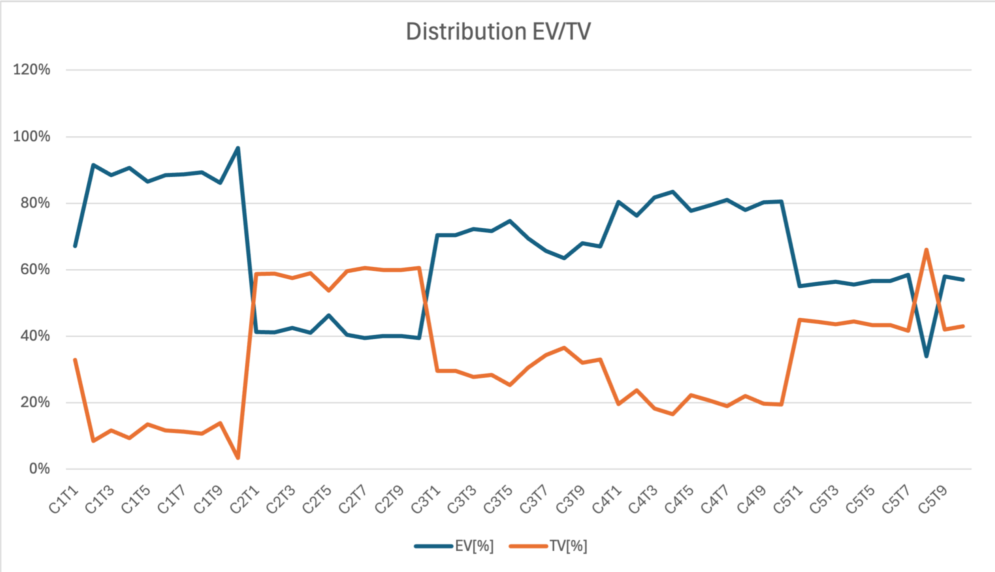

Figure 4.1: Distribution Percentage of Electric Vehicles and Traditional Vehicles, Cases 1 to 5

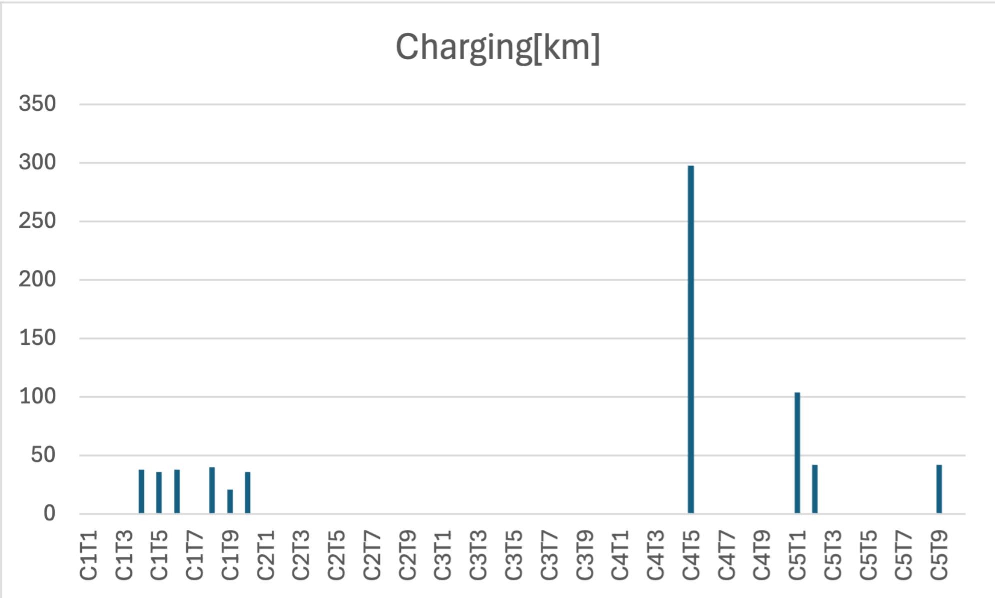

Figure 4.2: Charging Kilometers for Cases 1 to 5

4.3.2 Charging Incentive Scenarios (Cities 6-10)

For the segment of cities generated {6,7,8,9,10}, cases are aggregated with an incentive for charging use. This consists of a discount rate related to the energy charger during the total period with value $\gamma = 0.5$. The move is inspired by the charging use when the vehicles are not in service of passengers and cases of higher convenience of charging during the service period. The fixed discount doesn't represent a real-case value, selected for measure the behavior of the model. An example of this case is a transport system with solar energy, with a period-day which may result the less of costs to buy energy with contracts of own consumption. For formulate this concepts es added to the objective function the discount for operational recharge, shown in Equation 4.1. Also, the number of trips defined for this set of cities is higher than the initial ones, in the section4.3.1, and represents a variety of fleet composition.

$$Z = \sum_{u \in U} \sum_{k_u \in K_u} \Bigg(\sum_{i,j \in S, i \neq j} X_{ij}^{rk_u} c_u l_i \quad + \sum_{q \in Q} \sum_{i \in S} X_{qi}^{rk_u} c_u l_{qi} \\ + \sum_{q \in Q} \sum_{i \in S} X_{iq}^{rk_u} c_u l_{iq} \quad - w_{rk} \cdot \gamma \Big) \tag{4.1}$$

In the Equation 4.1, w_{rk} represents the amount of charge, with distance measure, consumed by a vehicle k on a cycle r.

Indicators of distribution between electric vehicles and traditional vehicles, displayed in the Figure 4.3 show two more clearly defined zones. For the city C6, the use of each type of vehicle source gives a certain type of equity, with, in most cases, higher use of electric vehicles. For the continuous four-city tests, the use of electric vehicles is stronger and near to a unique use of them. This leaves that even with a strong fleet of electric vehicles, the cases consider some uses of traditional vehicles.

About the charging management visible in the Figure 4.4, the incentive follows their limit generated for these cases by the charger use. The model behavior aims to use the electric vehicles in higher number of trips for charging after. These results coincide with the expected search of the model for the minimization of costs.

4.3.3 High Trip Volume Scenarios (Cities 11-15: No Charging Incentive)

Given the results of the Section 4.3.2, it is considered to evaluate whether with a higher number of trips and without incentives, as in the 4.3.1, to measure the charging decisions. The segment of cities {11,12,13,14,15} is also considered a new

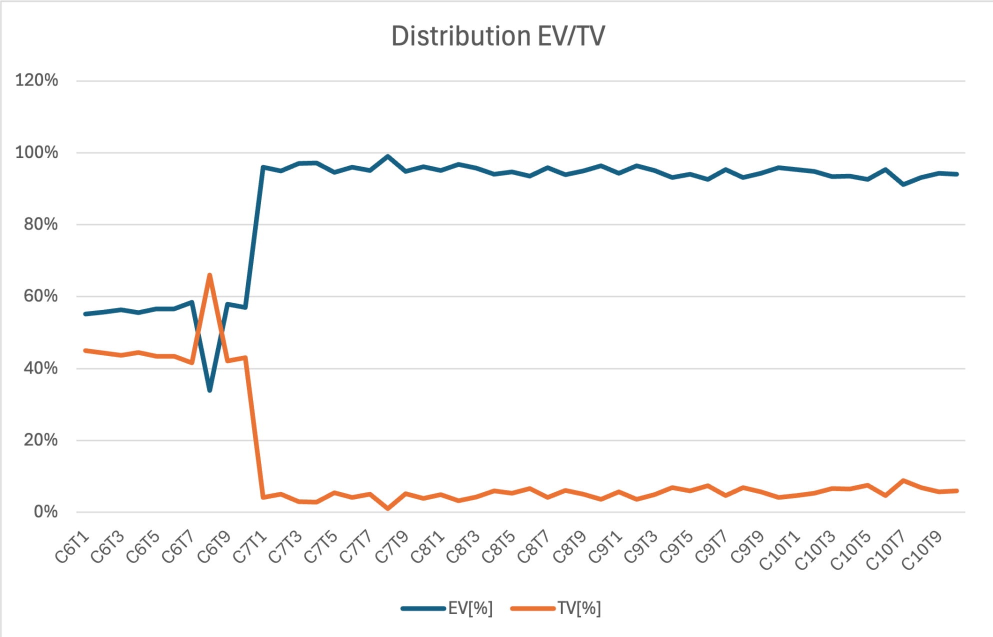

Figure 4.3: Distribution Percentage of Electric Vehicles and Traditional Vehicles, Cases 6 to 10

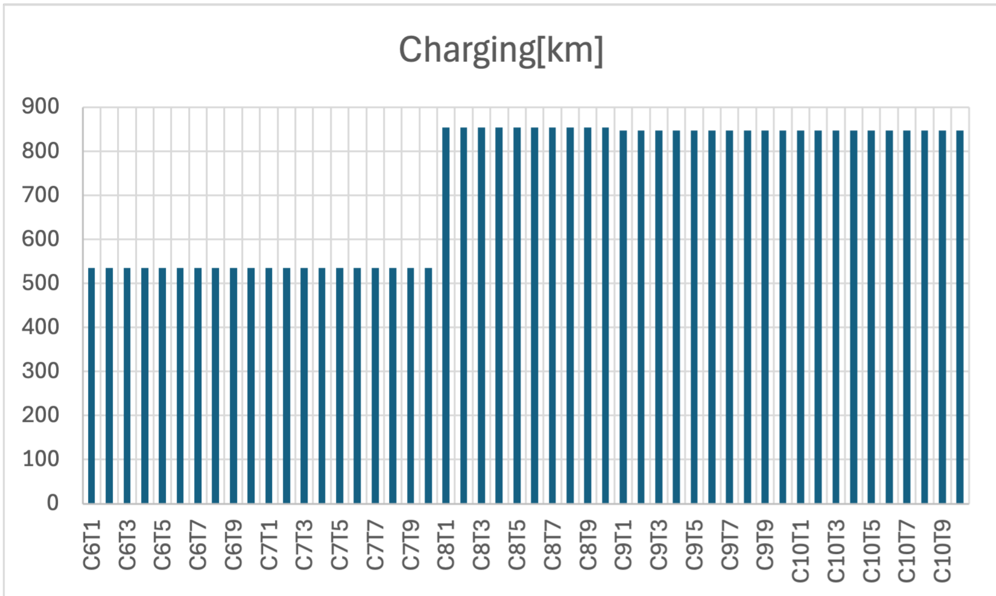

Figure 4.4: Charging Kilometers for Cases 6 to 10

depot available. The cases have similarity in most of the fleet compositions but with different large of trips, without considering C14.

The Figure 4.5 considers a considerably higher use of the electric vehicles given the capacity of the electric vehicles. Additionally, for the last city, C15, the use decrease shows the limit of the use and the necessity of incorporating traditional vehicles due to the number of trips generated.

For the charging actions, the Figure 4.6 incorporates an important use of the charger in the case C13 and C14, before the case C15 that uses the diesel vehicles. This signal demonstrated the point of change between the motivation of use the batteries vs the use of traditional vehicles for complete the define timetable.

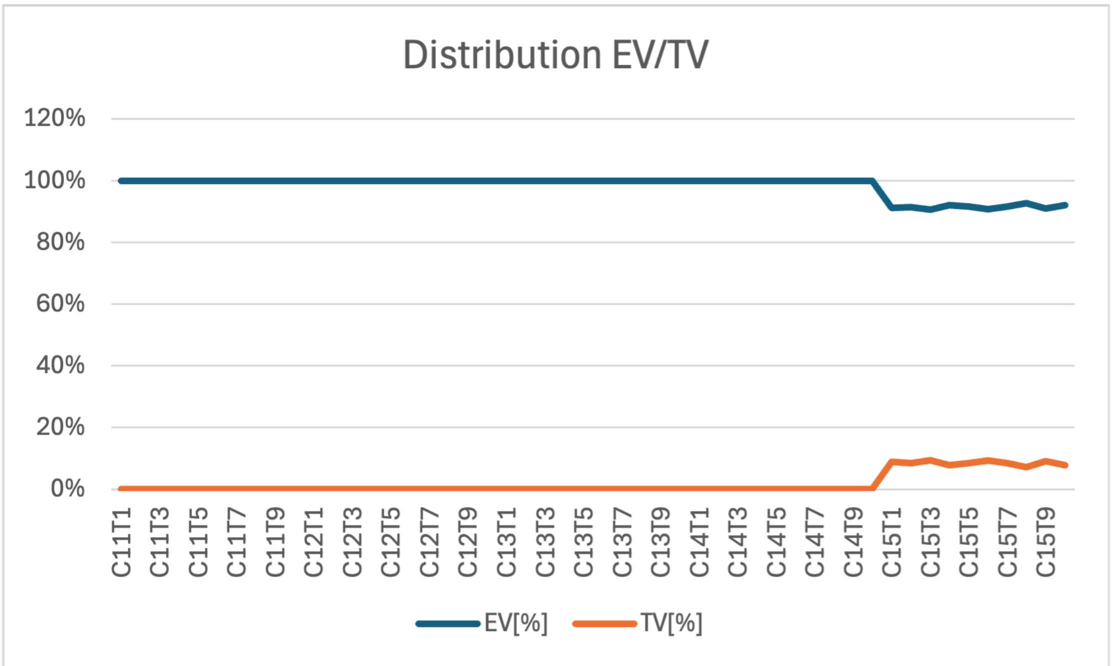

Figure 4.5: Distribution Percentage of Electric Vehicles and Traditional Vehicles, Cases 11 to 15

4.3.4 High Trip Volume with Incentive Scenarios (Cities 16-20)

For the last segment of cities, {16,17,18,19,20}, the program is stressed with a higher number of trips and the use of the incentive introduced in the Section 4.3.2. This generation utilized a homogeneous number of vehicles of each type and the same number of depots as the final Section 4.3.3. Despite the high number of trips, the use of electric vehicles is totally. For this level, the dependency of electric

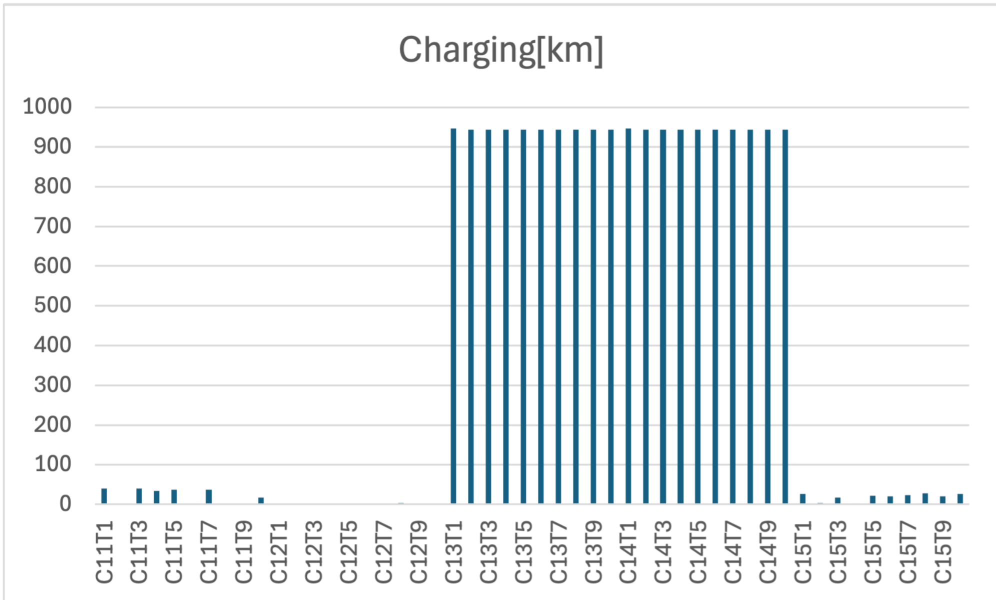

Figure 4.6: Charging Kilometers for Cases 11 to 15

vehicles is high, and the selection of charging doesn't follow changes. The limitation of charging during the period is presented by the incentive application.

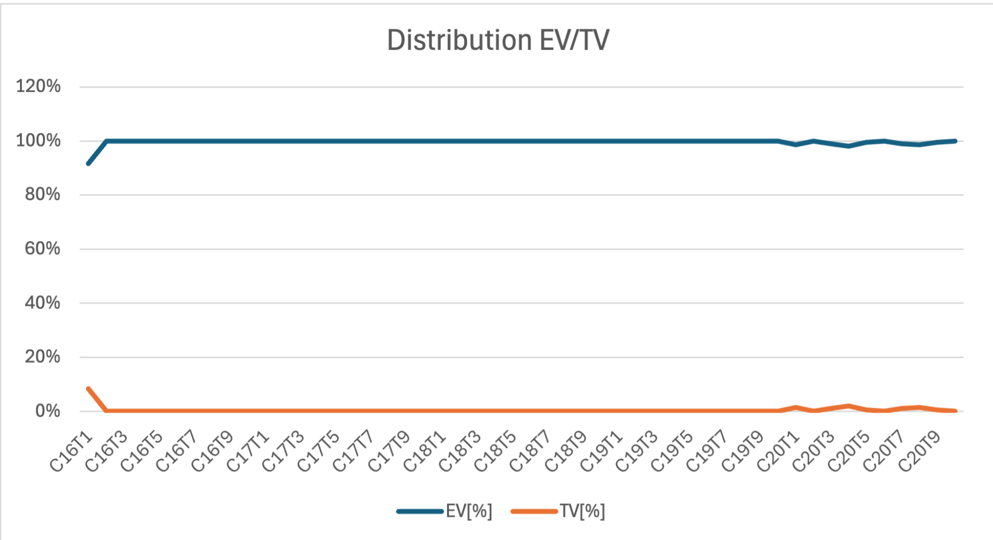

Figure 4.7: Distribution Percentage of Electric Vehicles and Traditional Vehicles, Cases 16 to 20

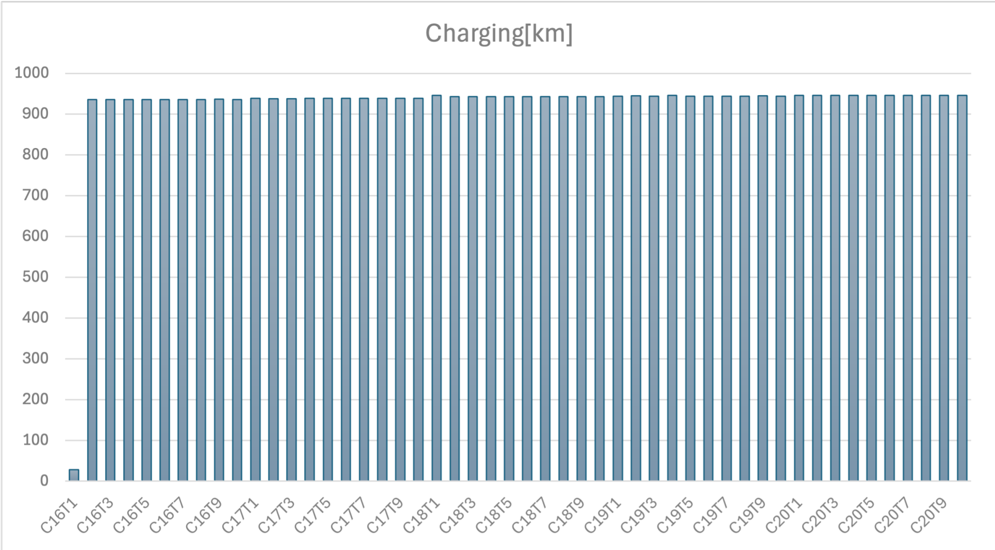

Figure 4.8: Charging Kilometers for Cases 16 to 20

4.3.5 Cross-referenced results

In light of certain cities are generated with the same amount of lines but under different scenarios, this section offers a comparative analysis between them. Table 4.4, introduce the average values of each city case in time and objective function value.

Comparison of C8, C9, and C10:

Cities C8 and C9 share the same number of trips. Their primary difference lies in the fleet's composition and size, specifically regarding the number of electric and traditional vehicles. The results show better performance in C9, which also features an additional electric vehicle. Both cities use the same range for the random generation of distances, although C8 exhibits a higher average solution time and deadhead kilometers. The average objective function value is lower in C9. These results demonstrate an increased benefit from using electric vehicles in the fleet, albeit with higher computational effort in scenarios like C8. Meanwhile, C10 has a similar number of trips but with a more diverse range of distances, which explains the higher objective function value in its evaluations.

Comparison of C11 and C18:

For the cases of C11 and C18, which have 130 lines and similar distance generation ranges, a marked difference in their results is observed. The evaluations show a higher average solution time in the case without incentive (presumably C11), and the expected decrease in the average objective function value for C18 (with incentive). For C11, charging levels do not exceed the equivalent of 20 kilometers for each vehicle; this is the minimum amount expected to reference the incentive's

City	Time[seg]	OF[EUR]
C1	60.629,3	45.178,9
C2	20.230,0	64.040,6
C3	5.553,5	63.703,3
C4	1.552,8	314.401,8
C5	2.499,4	234.465,0
C6	3.448,7	97.230,6
C7	1.887,6	118.242,1
C8	20.551,7	82.376,3
C9	4.605,2	43.273,6
C10	5.787,9	320.744,9
C11	28.763,0	479.782,7
C12	51.187,5	331.302,7
C13	260.12	251.326,7
C14	269.827,0	251.271,0
C15	291.097,5	459.818,1
C16	45.85	275.17
C17	13.08	282.62
C18	12.51	251.29
C19	16.775,3	336.493,6
C20	19.810,6	362.107

Table 4.4: Results of Objective Function and Computation Time

use, bringing levels to the maximum possible in some cycles. The distributions of deadhead by energy source demonstrate how the incentive aims to maximize the utilization of the electric vehicle to adhere to the timetable. However, the amount of deadhead kilometers does not significantly increase for C18.

Comparison of C13 and C14:

Cities C13 and C14 present very similar results. Their difference is found in the range of distances for trips. These results demonstrate that, with a similar scenario and this being the only constant difference, the optimal solution for both cities does not show significant changes in the decision variables. The solution time is slightly higher for C14, with an objective function value similar to that of C13.

Comparison of C12 and C19:

C12 and C19, generated with a similar distance range, present contrasting results under the difference in incentive scenarios. City C12, with a single charging case, relates its deadhead kilometers to electric vehicles. Charging decisions in C19 include high charging levels with a similar pattern. Like C12, C19's deadhead is generated by electric vehicles but with a low value. This point is interpreted as a prioritization of charging time at the depot compared to driving deadhead if it is not necessary to decrease the objective function value. The solution time is higher in C12, but the objective function value is higher in C19.

Chapter 5

Application and Data: Modeling Turin's Heterogeneous Bus Fleet

The multi-fleet consideration for the model is inspired by cities like Turin, Italy. The public transport company, Gruppo Torinese Trasporti (GTT), operates as a monopoly and its assets consist of vehicles powered by diesel, electricity, and natural gas. In 2022, the bus fleet composition was approximately 14% electric, 65% diesel, and 22% CNG, based on public information [31]. GTT announced plans to integrate 225 additional electric buses by 2023, increasing the proportion of electric vehicles to 63%. To evaluate the model's function, these proposed changes are considered by utilizing two types of fleets with representative proportions.

Given the city's size and the available resources for model evaluation, specific lines were selected to measure the model's behavior. These lines exhibit variable durations, frequencies, and minimal characteristics for the vehicles. Public information from GTT does not specify vehicle types for each trip. For the computational applications, routes from a general weekday were selected. The speed considered for driving is 15 km/hour with passengers and 20 km/hour without passengers. The maximum computational time for the program results is 600 seconds. Figure 5.1 illustrates the distribution of depots around the city. Table A.24 presents general characteristics of the city's depots. For test considerations, two depots with electric vehicle charging and storage infrastructure, Tortona and Gerbido, were utilized. More details from the lines and vehicles are in the Appendix A.4 and public information from GTT.

To evaluate both scenarios, the following concepts are considered:

Objective Function Value: The value obtained from the minimization of deadhead kilometers, considering the cost per kilometer based on the energy source used. This concept is introduced to measure the responses of both cases in achieving the objective.

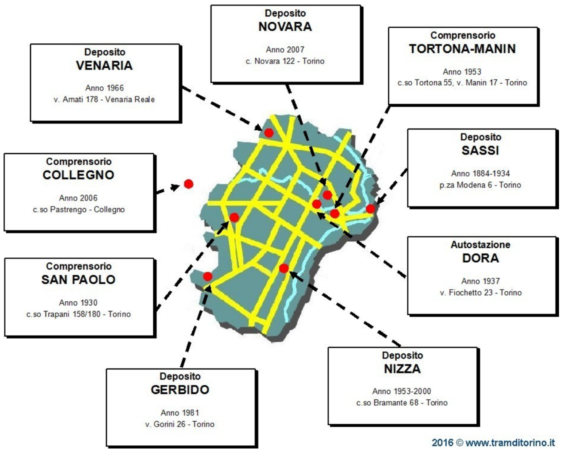

Figure 5.1: GTT Installations [31]

Depot	Energy Source	Capacity
Gerbido	CNG, Diesel and Electricity	300
Novara	CNG and Diesel	70
San Paolo	Diesel	74
Tortona	CNG, Diesel and Electricity	220
Nizza	Diesel	63
Venaria	Diesel	240
Collegno	Only Tram	-
Autostazione Dora	Temporary use	-
Fiochetto	Temporary use	-

Table 5.1: GTT Depots in Turin, 2022 [31]

Total Deadhead: Measured in kilometers driven by both electric and traditional vehicles. This metric is crucial for understanding the decisions made by the solver from the model.

Charge: The amount of energy charged by a vehicle at the start of a cycle. This measure allows us to ascertain if charging was required and to track the quantity in each case.

SoC: The State of Charge of electric vehicles for each cycle. From this point, it is possible to track battery levels throughout the period.

Kilometers by EVs: Deadhead kilometers completed by electric vehicles during the period. As a component of the Total Deadhead, this allows for consideration of the portion with lower cost and its relation to the electric energy source.

Kilometers by TVs: Deadhead kilometers completed by traditional vehicles during the period. As a component of the Total Deadhead, this reports the amount of distance with higher cost and its relation to traditional vehicles.

Time: The computational time spent by the solver to find a solution. As the cases vary by the density of electric vehicles, this provides an opportunity to understand the impact of constraints associated with this energy source.

Costs Depot-to-Trip: Percentage of cost related to the 'put-in' actions (i.e., movements from the depot to the first trip start point).

Costs Trip-to-Trip: Percentage of costs related to distances traveled by vehicles from the endpoint of one trip to the start of the subsequent trip.

Costs Trip-to-Depot: Percentage of costs related to 'put-out' actions (i.e., deadhead costs from a trip's end point to the assigned depot).

5.1 Single Line Analysis

As the model operates with trip-by-trip detail, four specific lines were selected to establish real-world test cases. All lines considered are two-directional, which simplifies the calculation of distances (e.g., by considering direct trip distances or zero distances for return legs where applicable). For each line, two cases are presented, distinguished by their respective electric and traditional vehicle compositions. The inspiration for these compositions is derived from proposed changes announced by GTT; however, the percentages are not exactly equal, primarily due to the larger fleet sizes that such exact replication would necessitate (e.g., a minimum of five vehicles for short lines). For simplification, traditional vehicles are considered to have unlimited availability. As will be seen in the results, this assumption does not significantly affect the outcomes due to the considerable price difference between energy source types. For the single-line cases and depots with available electric charging, it is assumed that all vehicles are assigned to a unique depot.

5.1.1 Line 73

This line, operated by GTT, is currently assigned to electric buses. It is characterized by its short distance and low trip frequency. During a weekday, it has a total of 42 trips, each with a distance of 5.5 kilometers. Consequently, the vehicle selected from the GTT fleet is the Cacciamali Elfo, which has an available range of 104 kilometers (representing 60% of its full autonomy). The assigned depot is Tortona, which aligns with the actual use of this vehicle type. Figure 5.2 presents the route of this line. For this case, the fleet comprises three vehicles. The first scenario utilizes two traditional vehicles and one electric vehicle, while the second scenario includes two electric vehicles and one traditional vehicle. These distinct fleet compositions enable a comparative analysis of the cases.

Figure 5.2: Route Line 73

Given the lower cost per kilometer for electric vehicles, a decrease in deadhead costs is an expected outcome. Table 5.2 presents the objective function values. For the same set of trips, the fleet with more electric vehicles achieves a lower operational cost. The results demonstrate that, for this case, the use of electric vehicles allows for the selection of routes with lower associated costs, and efficiently reduces the total kilometers traveled across the fleet. The distribution of deadhead costs represent an increment in the depot-trip and trip-depot, explain by the availability of electric vehicles for accomplish routes longer but with a less cost associated and with the possibility of increase the kilometers feasible by these vehciles.

Figure 5.3 illustrates the distribution of trips and deadhead kilometers per vehicle. The charging decision successfully representation coincides with the schedule, this model doesn't generate schedule charging. Regarding cost distribution, movements between trip points represent the largest proportion of deadhead costs. This is particularly relevant when electric vehicles visit the depot for charging. Figure 5.4 represents the SoC values reported at the start of each cycle for the vehicle. Based on this information, it is understood that the charging decision is made for cycle 2. This coincides with Figure 5.5, which represents the amount of charge executed.

In the second case, the expenses associated with 'put-in' and 'put-out' decisions increase. This is explained by the charging decision and the increased cost for the traditional vehicle to complete its cycle, as demonstrated in Figure 5.6. The State of Charge (SoC) of both vehicles in Figure 5.7 indicates the charging decision for cycle 2. To balance the available range for cycle 2, the vehicle is required to charge prior to commencing trips. As the energy level at cycle 1 is low, the amount of charge, as shown in Figure 5.8, increases to the required level. The SoC in both cases remains below or equal to the imposed maximum.

Fleet	**1st**	**2nd**
Objective function value	68.85	44.99
Total Deadhead	150.34	100.40
Charging	[99.0]	[66.00, 82.5]
SoC	[104.0, 5.0, 87.49]	[104.0, 37.99, 104.0, 104.0, 21.5, 104.0]
Kilometers by EVs	100.71	74.12
Kilometers by TVs	49.63	26.27
Time[seconds]	0.1087	0.1090
Costs		
Depot-to-trip	19.5%	21.2%
Trip-to-trip	61.1%	47.6%
Trip-to-Depot	19.5%	31.1%

Table 5.2: Results of Line 73

5.1.2 Line 78

Similar to Line 73, this line is part of GTT's electric routes. During a weekday, this route is operated 48 times. It has a relatively low duration, and each trip is characterized by a distance of 3.25 kilometers. Figure 5.9 illustrates the route, including its related stops. Figure 5.9 defines the route with the stops related to this line. The assumed depot is Gerbido, based on its proximity. Given the trip distance, the fleet for testing is the same as that used for Line 73, as described in Section 5.1.1.

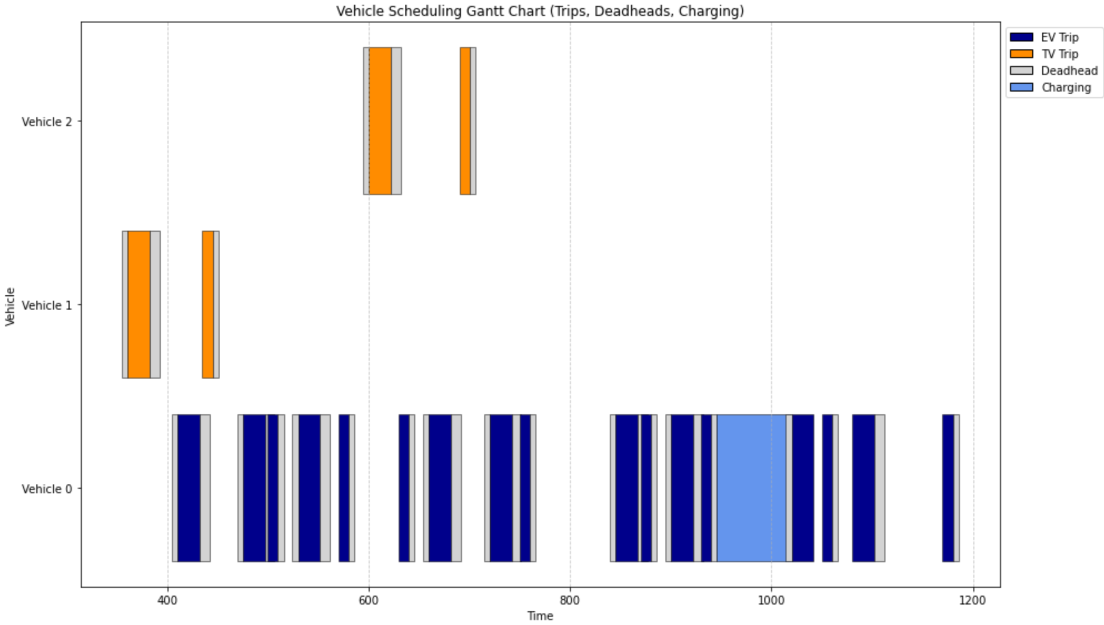

Figure 5.3: Gantt Line 73, Case 1

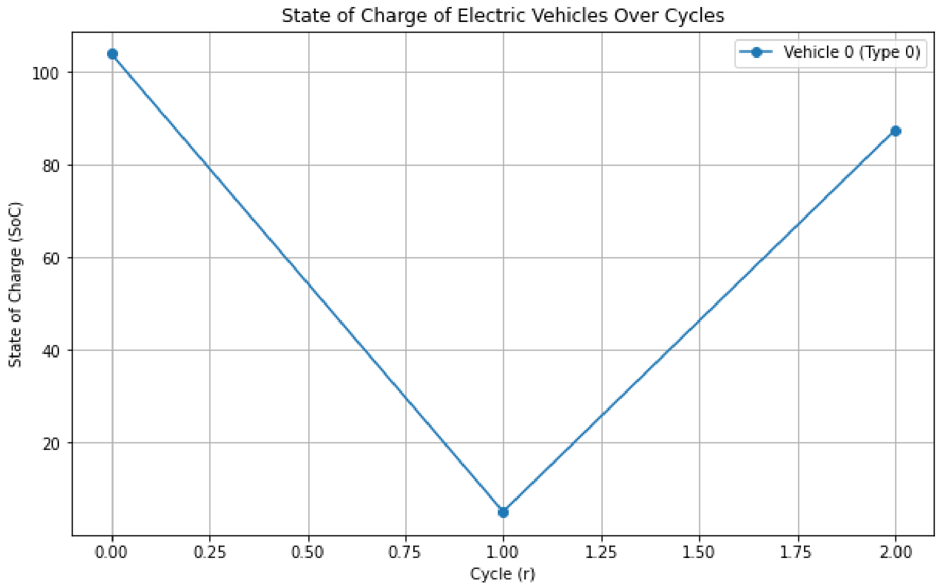

Figure 5.4: SoC of Line 73, Case 1

The results in Table 5.3 demonstrate a consistent decrease in the objective function value when using a fleet composed of a higher number of electric vehicles. Both cases do not require charging actions, and vehicles operate through their full

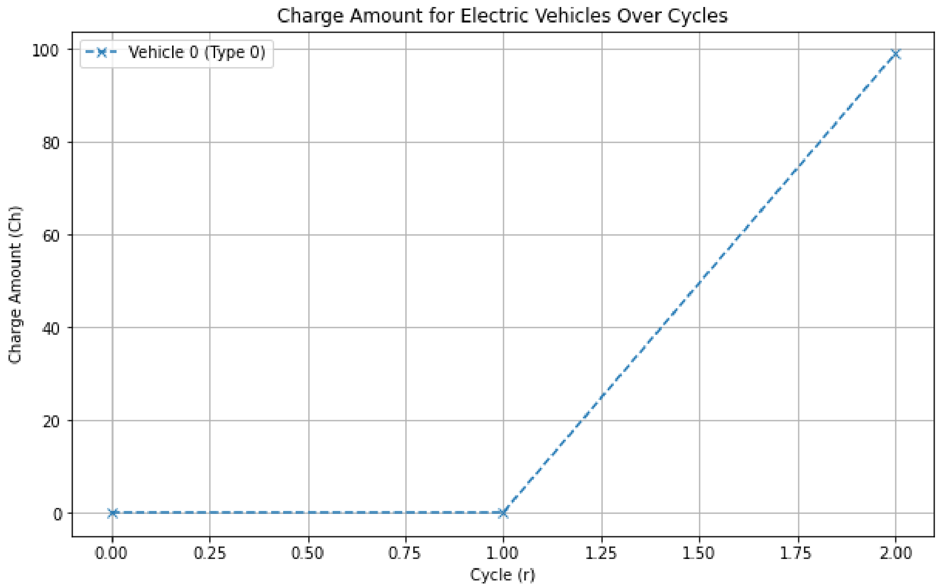

Figure 5.5: Charger Line 73, Case 1

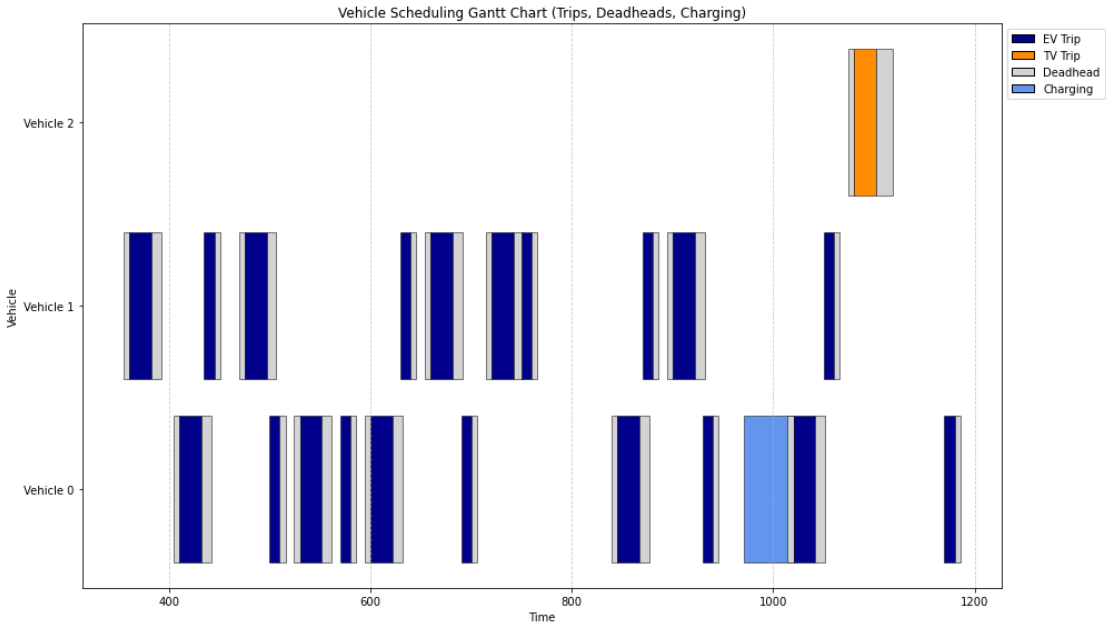

Figure 5.6: Gantt Line 73, Case 2

available range, concluding with their last cycle. The expenditure in deadhead kilometers increases, particularly for movements between trip points, as the model prioritizes the use of the lower-cost electric vehicles, even if it entails longer deadhead

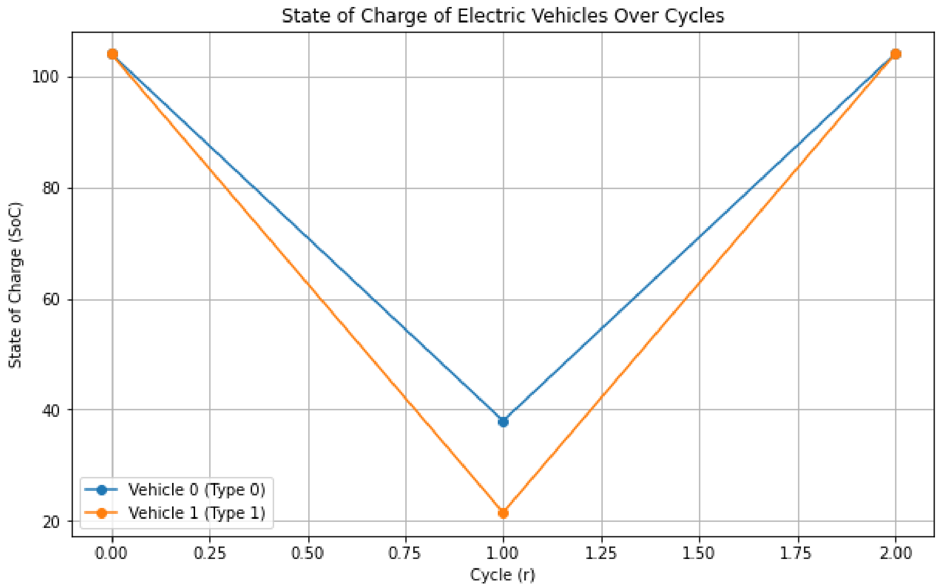

Figure 5.7: SoC of Line 73, Case 2

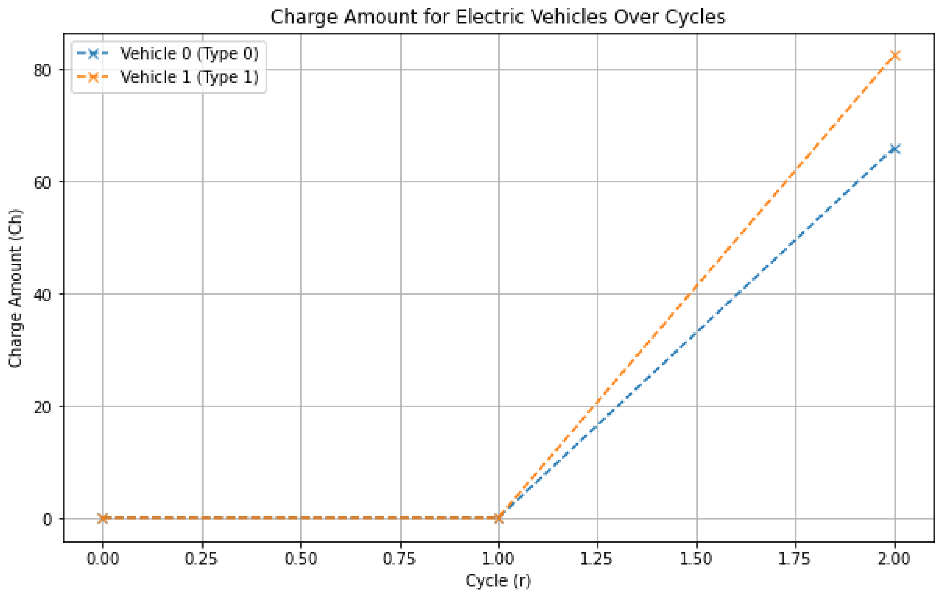

Figure 5.8: Charge of Line 73, Case 2

distances. Given the characteristics of

Figure 5.10 presents the preference for using electric vehicles, relegating traditional vehicles to an auxiliary role. For the second case, Figure 5.11 shows a

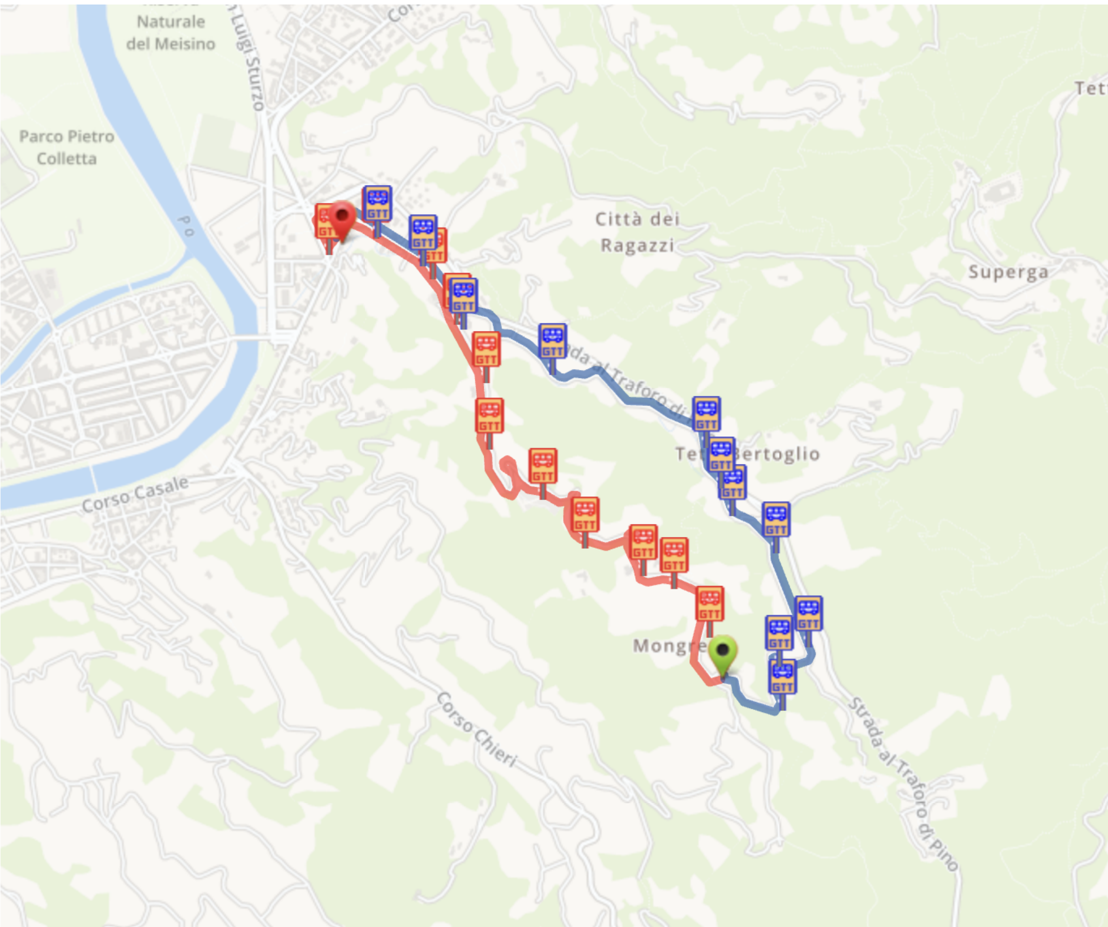

Figure 5.9: Route Line 78

broader distribution of trips across the vehicles. Even for this relatively simple case, it is possible to appreciate the realistic decisions represented in the model's solution with real data. Exist a decrease in kilometers deadhead Depot-to-trip and Trip-to-Depot, explain for decrease of cost by follow distances Trip-to-trip and the search of assign the maximum amount of trips to electric vehicles.

5.1.3 Line 58

For testing the model on longer and more frequent routes, Line 58 is considered. On a weekday, this route has a frequency of 190 trips. Each trip has a distance of 29 kilometers, as presented in Figure 5.12. Currently, the assigned depot for this line is Gerbido. Considering the characteristics of the trip, the electric vehicles in the fleet are represented by the BYD K7 model. This vehicle has an available range

Fleet	**1st**	**2nd**
Objective function value	49.23	43.61
Total Deadhead	37.54	60.22
Charging	[]	[]
SoC	[104.0, 104.0, 104.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 18.24]]
Kilometers by EVs	27.70	49.72
Kilometers by TVs	9.84	10.50
Time[seconds]	0.8804	0.5973
Costs		
Depot-to-trip	14.3%	10.6%
Trip-to-trip	71.4%	78.8%
Trip-to-Depot	14.3%	10.6%

Table 5.3: Results of Line 78

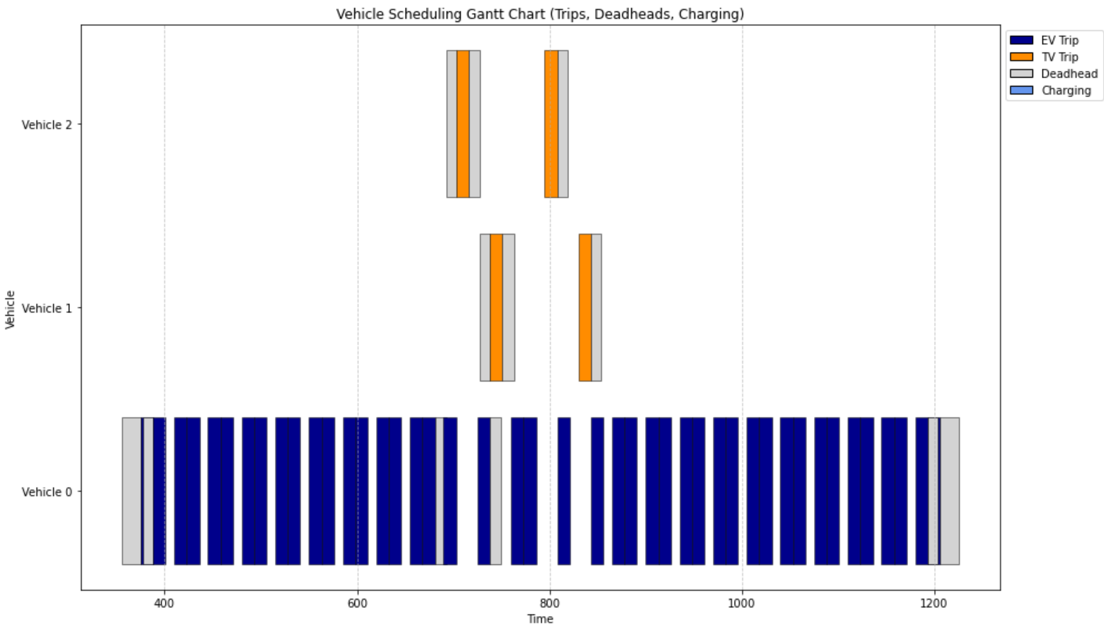

Figure 5.10: Gantt Line 78, Case 1

of 229 kilometers (considering 60% of its full autonomy). The depot's assignment coincides with the vehicle model's current deployment. This description is provided due to the lack of solutions found when using fleets with less battery range.

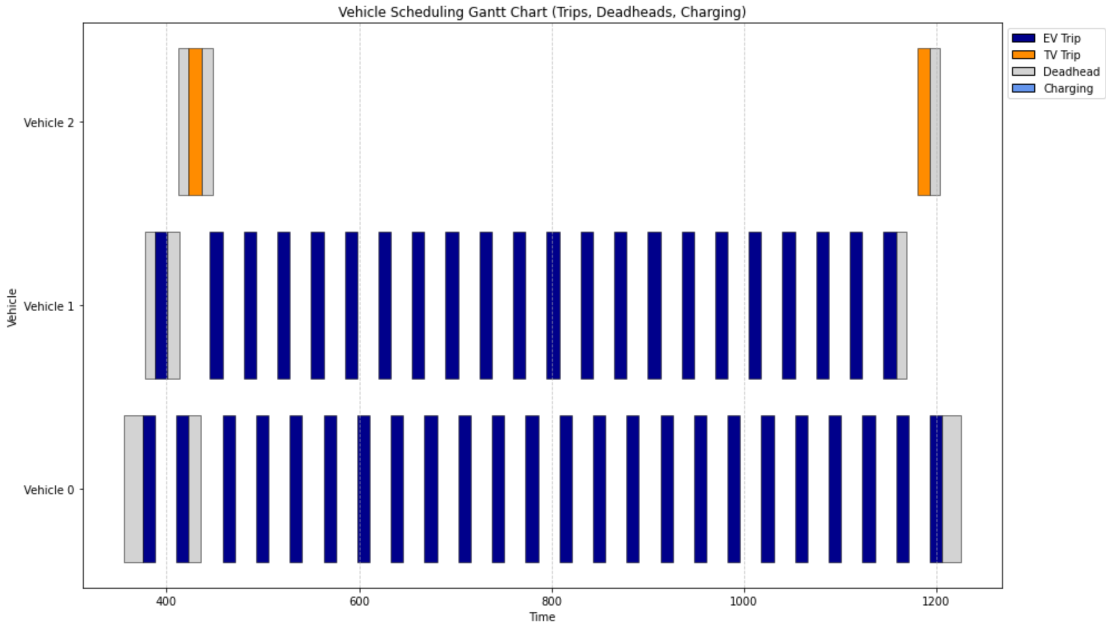

Figure 5.11: Gantt Line 78, Case 2

In both cases, the fleet consists of six vehicles. The first case includes two electric vehicles and four traditional vehicles, while the second case comprises five electric vehicles and one traditional vehicle. It is important to note that a fleet composition of four electric vehicles and one traditional vehicle resulted in no feasible solutions within the available time limit.

Table 5.4 presents the model's results for both cases. As expected, the use of electric vehicles decreases the objective function values due to their lower operational costs. The charging requirements are zero for both cases. While the total deadhead kilometers do not significantly decrease, their composition changes considerably, with a higher proportion covered by electric vehicles (as shown in Kilometers by EVs/TVs). The computational time limit was exceeded for both cases, indicating that the presented solutions are the best found within the allocated time, rather than necessarily optimal. The distribution of costs for deadhead movements remains similar, with a slight increase in costs for movements between trips.

The distribution of trips and deadhead actions during the period is shown in Figure 5.13. Electric vehicles exhibit a strong preference for performing trips, although the routes allotted to conventional vehicles also exhibit comparable operational patterns. In the second scenario, Figure 5.14 demonstrates the increased preference for electric vehicles, with traditional vehicles utilized in an auxiliary capacity.

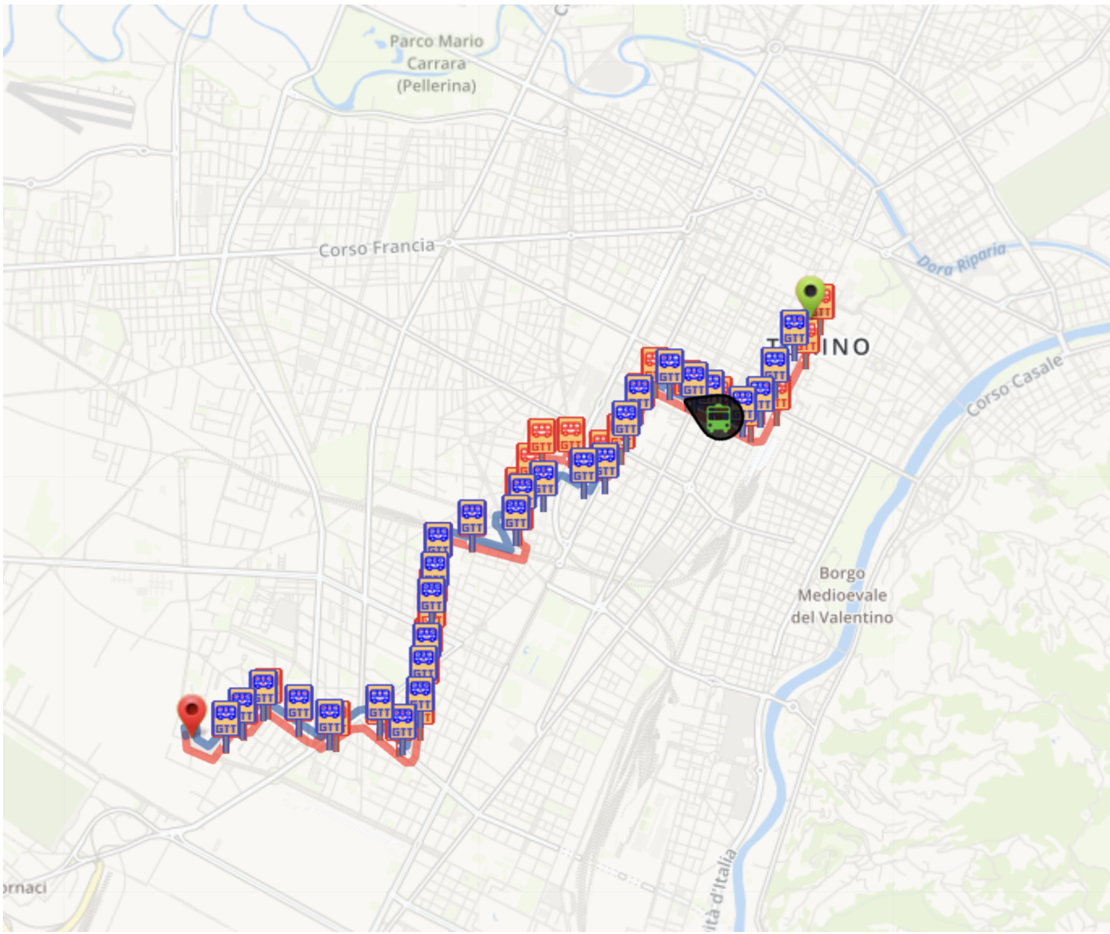

Figure 5.12: Route Line 58

5.1.4 Line 2

As one of the longer routes with higher frequency, line 2 represents one of the more complex routes to apply to the model. The distance characterizing this route is 15 kilometers. On a weekday, the frequency of this line is 149 trips. According to information from GTT, some electric vehicles are currently used on this line. Considering the features of this line, the electric vehicle used is the model BYD K9. This vehicle has an available distance of 229 kilometers (considering the 60% of autonomy). The depot assigned for this line is Gerbido.

The results in Table 5.5 demonstrate how the model responded to the increased demands imposed by the line's characteristics. The objective function values show a decrease in cost related to deadhead kilometers. This is achieved through a higher utilization of electric vehicles and strategic charging actions, which lead to a slight increase in costs associated with trip-to-depot movements.

Fleet	**1st**	**2nd**
Objective function value	1030.82	410.45
Total Deadhead	231.325	229.23
Charging	[]	[]
SoC	[229.0, 229.0, 229.0, 229.0, 229.0, 229.0]	[229.0, 229.0, 229.0, 229.0, 229.0, 229.0, 229.0, 229.0, 1.82, 229.0, 229.0, 229.00, 229.0, 229.0, 229.0]
Kilometers by EVs	118.48	155.13
Kilometers by TVs	112.83	74.10
Time[seconds]	600	600
Costs		
Depot-to-trip	6.1%	5.2%
Trip-to-trip	87.8%	89.4%
Trip-to-Depot	6.1%	5.4%

Table 5.4: Results of Line 58

Figure 5.17 demonstrates high utilization of the electric vehicle, potentially indicating that certain operational constraints (such as minimum time between trips or charging windows at the depot) are not fully met. The charging period is not directly integrated with deadhead actions. Furthermore, the significant distance and duration of each trip present a high operational challenge, making it difficult to find a feasible solution with the current fleet size. During testing, even introducing more vehicles resulted in unfeasible solutions. Considering these challenges, the solver adopts a simplified approach to identify a solution, even if it does not fully meet all the desired characteristics or optimal conditions.

The solutions generated by the solver for this case are presented in the following figures. Figure 5.17 shows the State of Charge information at the beginning of each cycle, demonstrating the utilization of both electric vehicles across multiple cycles. This aligns with the charging actions displayed in Figure 5.18, specifically for Vehicle 0 in Cycle 2.

To understand the behavior with a higher number of electric vehicles, Case 2 is examined. Figure 5.19 illustrates a high density of trips assigned to the vehicles. However, the charging periods do not fully coincide with available idle times or the

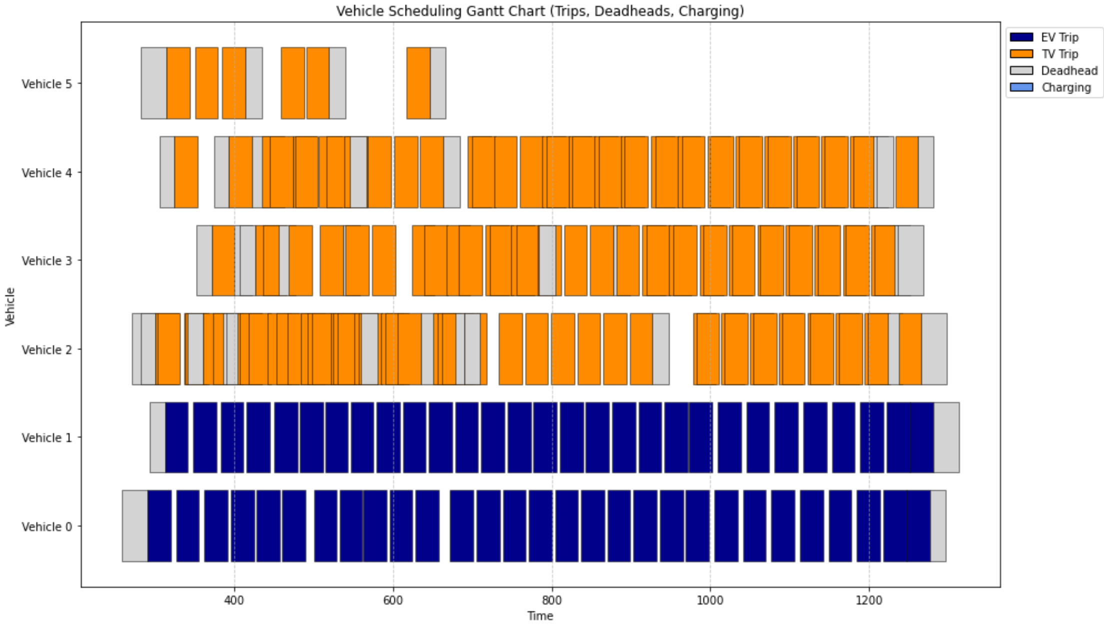

Figure 5.13: Gantt Line 58, Case 1

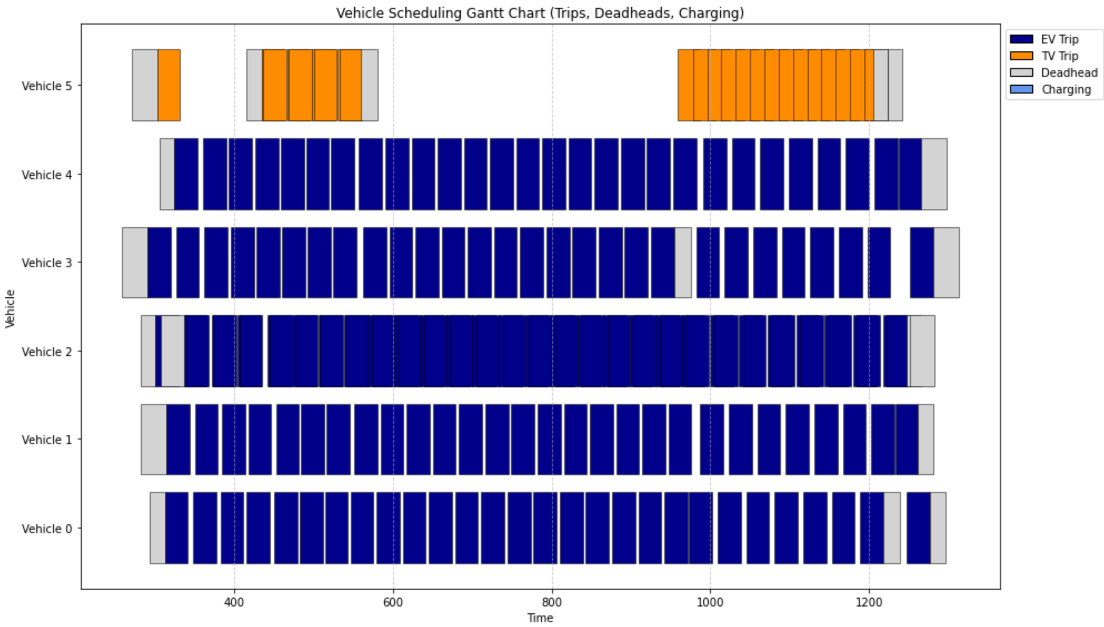

Figure 5.14: Gantt Line 58, Case 2

physical limitations of the charging infrastructure. The State of Charge information in Figure 5.20 reveals the varied utilization of each cycle by the vehicles. For vehicles

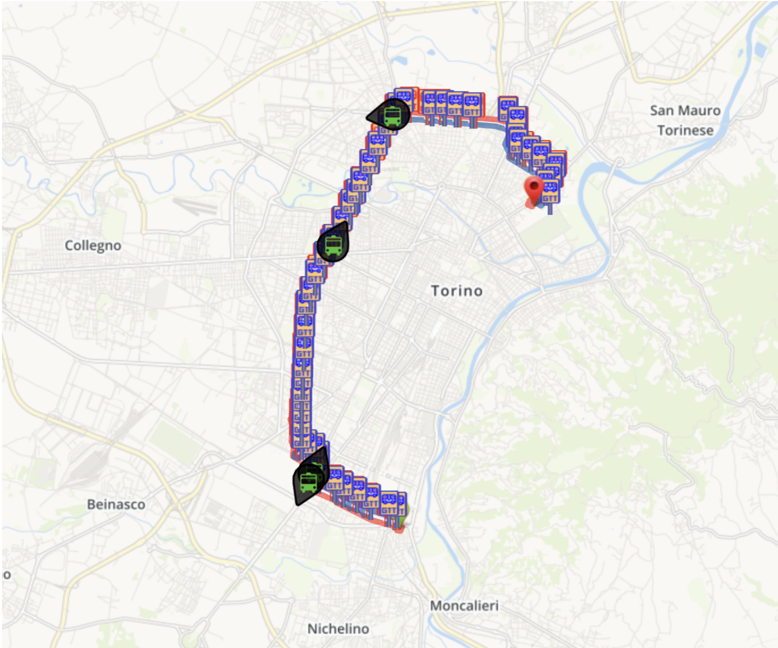

Figure 5.15: Route Line 2

0 and 1, no charging instance is required, indicating their ability to complete cycles 1 and 2, respectively, without intermediate charging. Conversely, vehicles 2 and 3 require charging, as depicted in Figure 5.21, to complete their two assigned cycles, both starting from Cycle 0.

5.2 Double Lines Analysis

Building upon the results from the single-line analysis, two scenarios involving two lines are now explored. The increase in complexity for each additional line, particularly concerning the detailed distances between depots (related to a key decision variable), is noteworthy. Furthermore, adding more lines necessitates a more precise definition of distances between depots and both trip start and end points. Both of these considerations are directly linked to decision variables. This simplification aims to streamline the pre-processing information for the model in future work. This type of approach is commonly suggested in the literature for finding solutions to large-scale problems, such as column generation. The following test considers two lines operating on a regular day. The depot is simplified by the same assignment for both lines.

For this section, the test involved more than one line. As this process considers a detailed timetable rather than the use of reduced routes, the addition of each line

Fleet	**1st**	**2nd**
Objective function value	819.13	755.94
Total Deadhead	847.73	738.15
Charging	[191.10]	[220.35, 181.36]
SoC	[229.0, 37.89, 229.0, 229.0, 229.0, 4.74]	[229.0, 229.0, 5.78, 229.0, 229.0, 229.0, 229.0, 8.64, 229.0, 229.0, 47.63, 19.74]
Kilometers by EVs	254.81	264.22
Kilometers by TVs	592.91	473.92
Time[seconds]	600	600
Costs		
Depot-to-trip	11.4%	10.1%
Trip-to-trip	76.6%	76.9%
Trip-to-Depot	12%	13%

Table 5.5: Results of Line 2

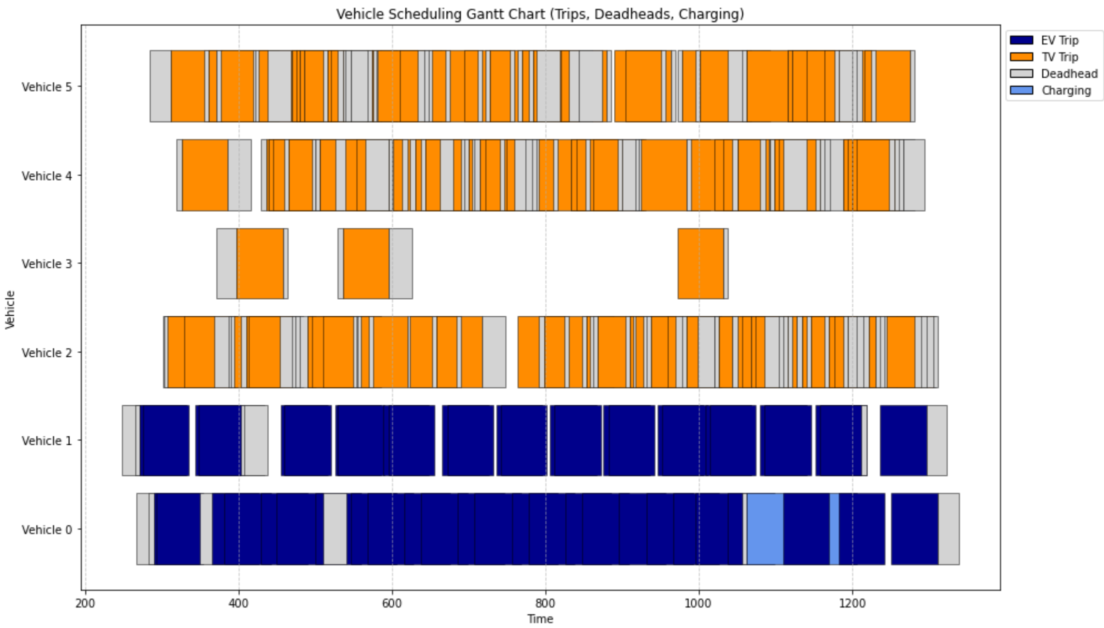

Figure 5.16: Gantt Line 2, Case 1

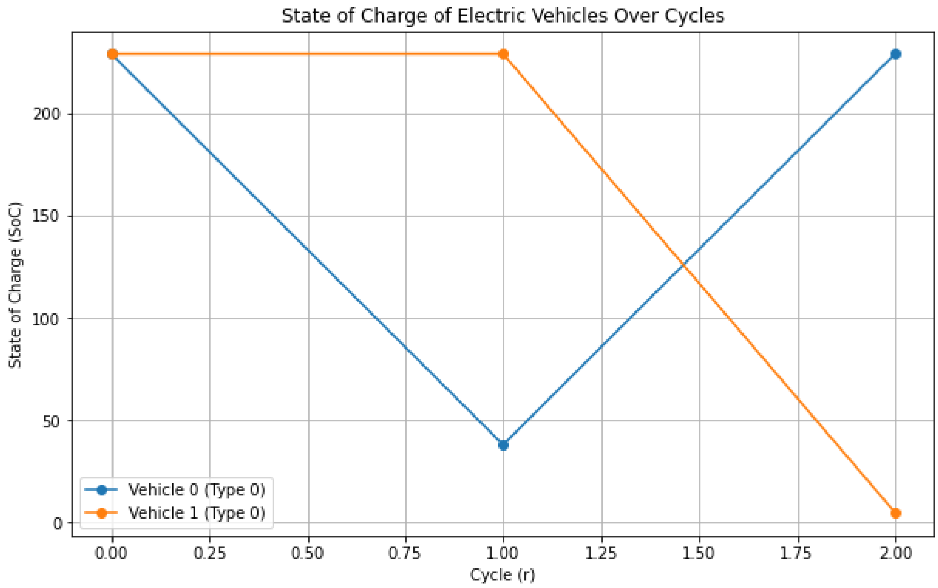

Figure 5.17: SoC Line 2, Case 1

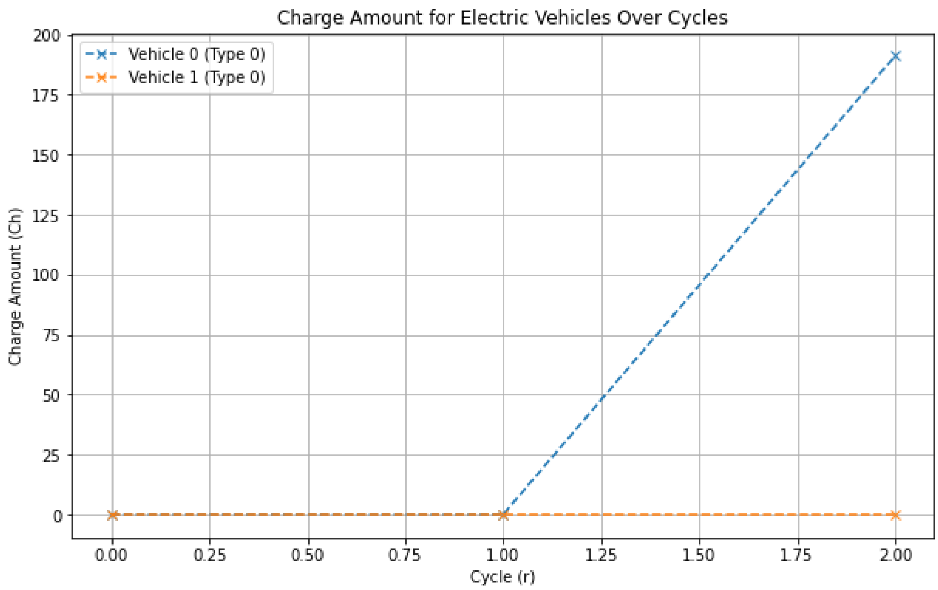

Figure 5.18: Charge Line 2, Case 1

or the presence of numerous trips significantly impacts the model's computational time and results.

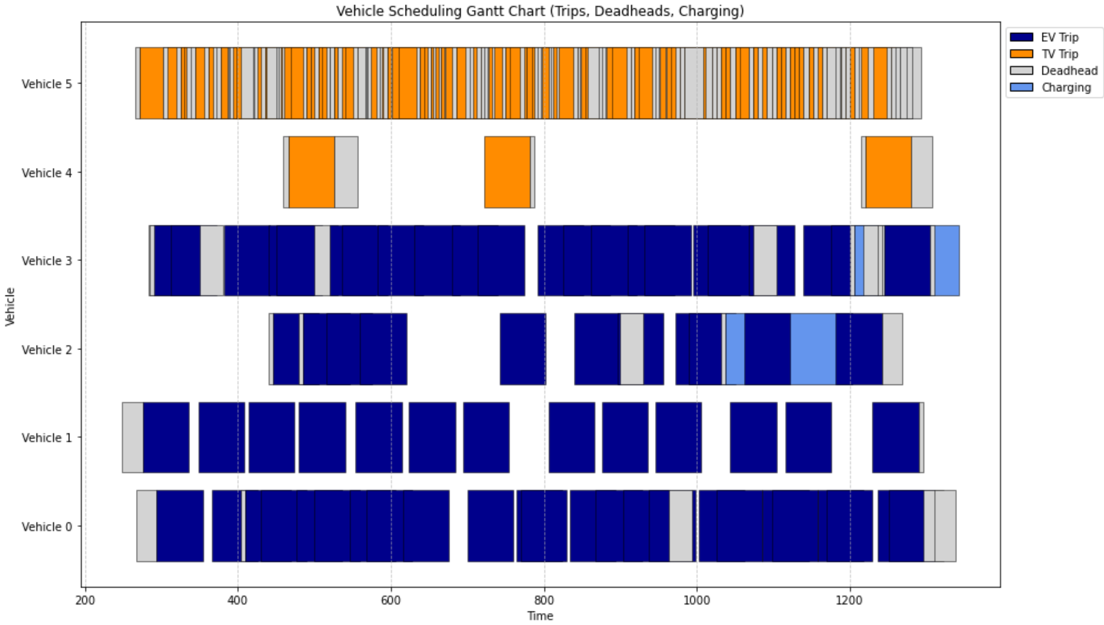

Figure 5.19: Gantt Line 2, Case 2

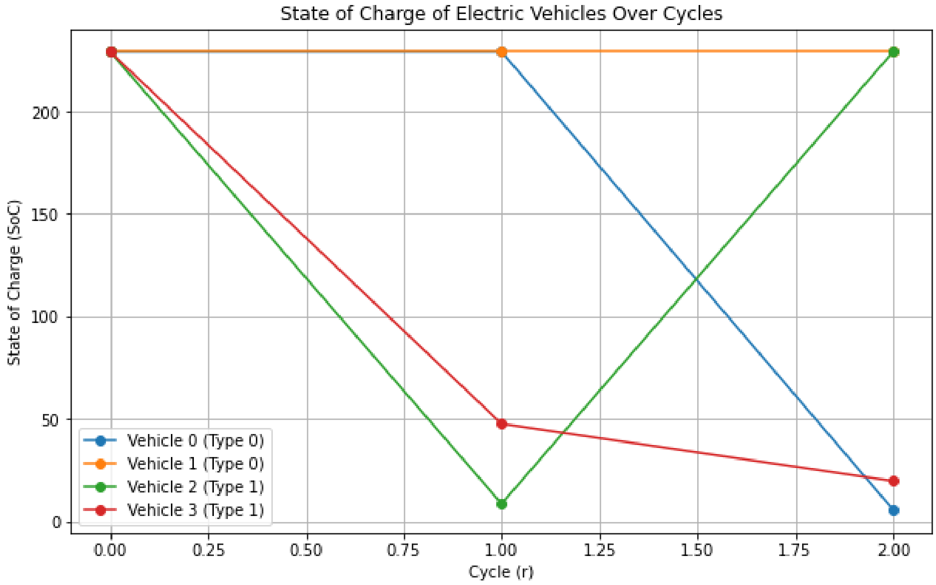

Figure 5.20: SoC Line 2, Case 2

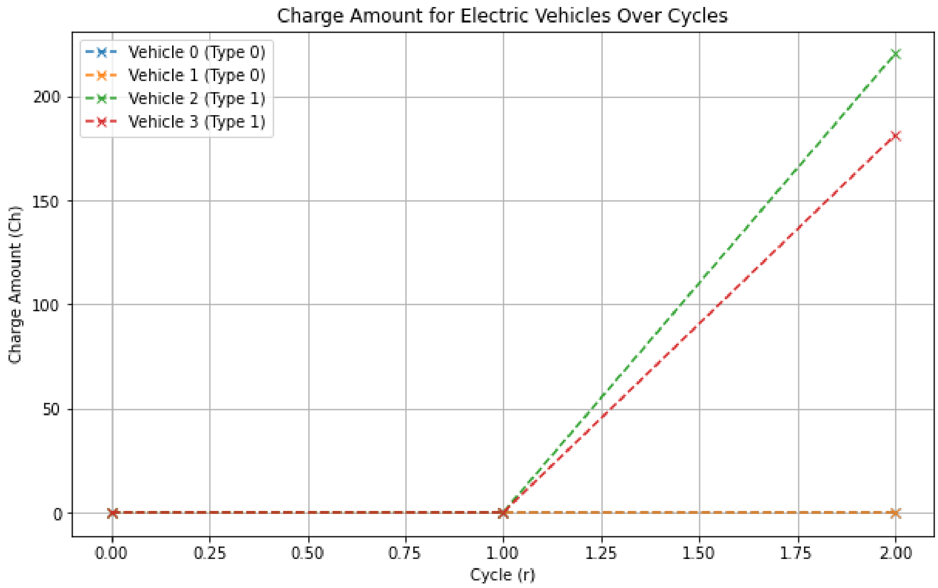

Figure 5.21: Charge Line 2, Case 2

5.2.1 Lines 73 and 78

The combination of these compatible lines, which share a common depot, creates a timetable with a total of 70 trips per day. However, these trips do not share similar characteristics (e.g., origin-destination, duration). The distance between the start and end points of the lines varies from 3.23 to 9.94 kilometers. The assigned depot is Tortona, with distances ranging from 1.87 to 10.90 kilometers. The routes of lines 73 and 78 are given in Figure 5.2 and Figure 5.9, respectively. The selected fleet composition uses the BYD 9 model, which has an available range of 229 kilometers (considering 60% of its total autonomy). For the first case, the fleet consists of only one electric vehicle and two traditional vehicles. For the second case, the composition includes one traditional vehicle and two electric vehicles.

The results in Table 5.6 show a decrease in the total deadhead cost attributed to the increased availability of electric vehicles for the line. The value in electric vehicle deadhead cost is allows to cover more kilometers with a lower operational cost. While the total objective function value decreases, the proportional contribution of depot-to-trip and trip-to-depot distances shows a slight increment, which is offset by other cost efficiencies in accomplishing certain routes. The spent time is significantly higher in the first case, this can be explain for the maximum use search for the one electric vehicle. The State of Charge(SoC), demonstrate a use of one cycle for both cases, but with the difference of a charging action for the second case.

Figures 5.22 and 5.23 illustrate the distribution of trips by vehicle. They present a second case with auxiliary use of traditional vehicles. Nevertheless, for the first case, their use is crucial to cover the required trips/demands. The charging profile is representative, as this model doesn't generate a charging schedule. However, given the reported charge values, it's evident that charging isn't utilized during the operational period, suggesting that actual charging might occur at the end of the day. This behavior indicates that the charger is only used when necessary or feasible.

Fleet	**1st**	**2nd**
Objective function value	90.56	63.94
Total Deadhead	120.1	241.55
Charging	[]	[5.67]
SoC	[229.0, 0.83, 0.83]	[229.0, 32.24, 0.0, 229.0, 15.28, 15.28]
Kilometers by EVs	60.86	212.02
Kilometers by TVs	59.33	29.52
Time[seconds]	13.4001	1.1705
Costs		
Depot-to-trip	10.7%	12.1%
Trip-to-trip	78.8%	71.8%
Trip-to-Depot	10.6%	16.1%

Table 5.6: Results of Lines 73 and 78

5.2.2 Lines 70 and 73

The integration of these two lines results in a timetable of 58 trips during a weekday scenario. Line 70 is characterized by a driving distance of 12.5 kilometers; its route is presented in Figure 5.24. The details of Line 73 are defined in Section 5.2. Their assigned depot is Tortona, with distances ranging from 1.47 to 10.90 kilometers. A distance exists between the initial and final points of trips, ranging from 2.62 to 15.94 kilometers. Given the longer distance of Line 70, the selected model to represent the electric buses is the BYD K9, with an available range of 229 kilometers (considering 60% of its total autonomy). For the first case, the fleet consists of only one electric vehicle and two traditional vehicles. For the second case, the composition includes one traditional vehicle and two electric vehicles.

As shown by the results in Table 5.7, it is evident that with the long-range battery buses, no charging is required. The deadhead kilometers between trips

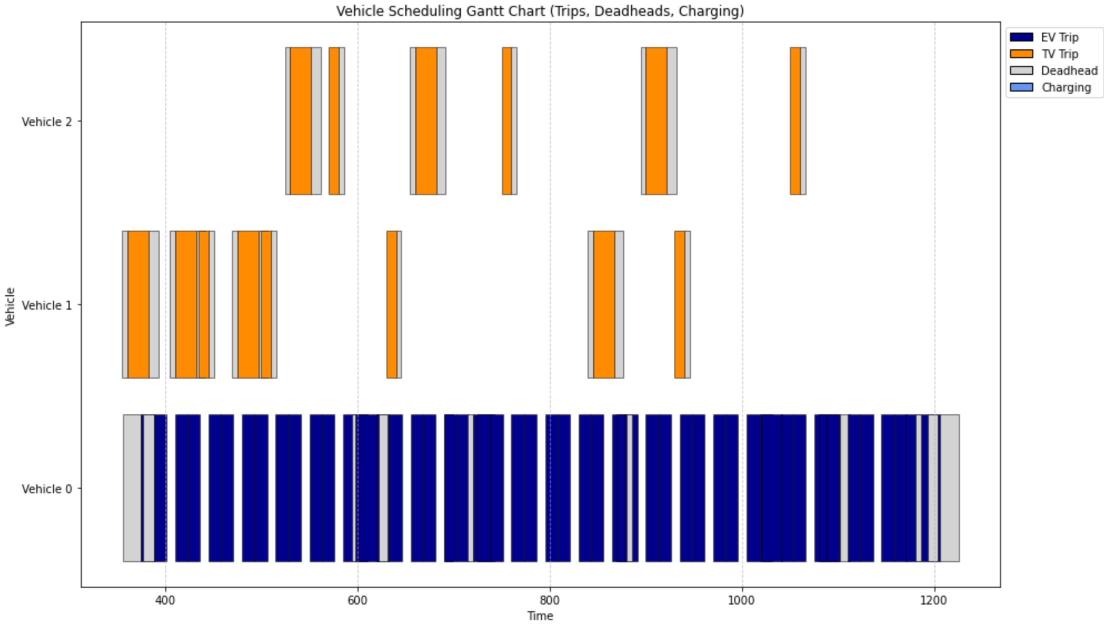

Figure 5.22: Gantt Lines 73 and 78, Case 1

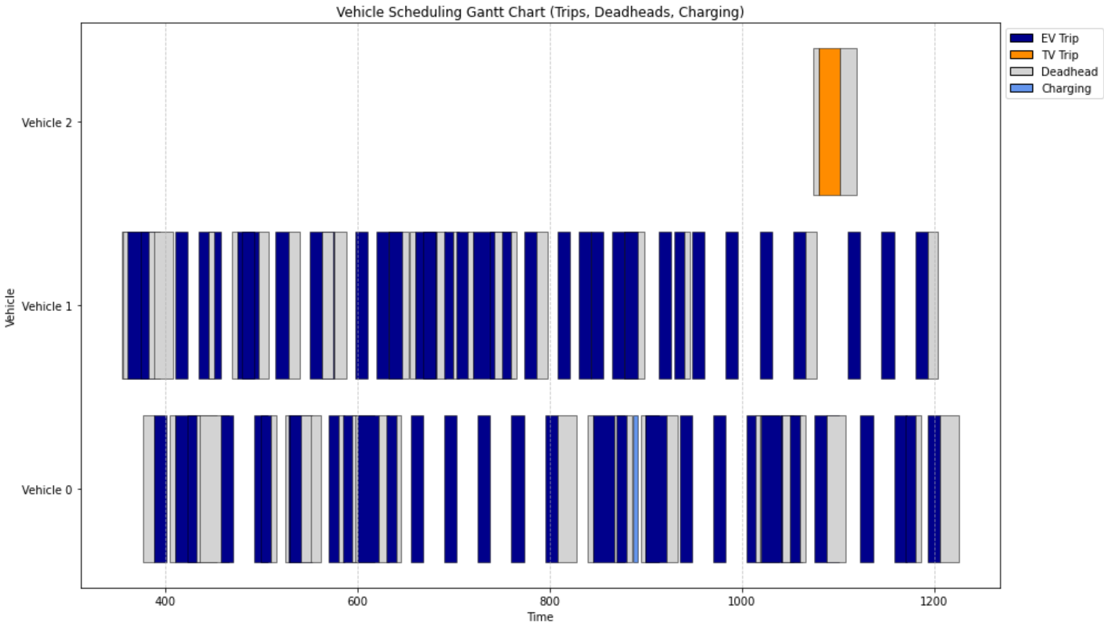

Figure 5.23: Gantt Lines 73 and 78, Case 2

increase due to the higher flexibility of this fleet, which enables the model to achieve the timetable using lower-cost kilometers (e.g., maximizing EV use where

Figure 5.24: Route Line 70

cost-effective), considering the overall cost distribution. This point explain the decrease in the objective function value for the second case. The time spent for the first case is minor than the second case, given the complexity of selection values for the amount of variables related to the electric vehicles. The State of Charge (SoC), inform for an only one cycle use, without charging actions in both cases.

Figures 5.25 and 5.26 provide a visual representation of trip distribution by vehicle. For this combination of lines, the traditional vehicle serves as an auxiliary component. The presence of traditional vehicles allows for the completion of timetable requirements in scenarios with a partial electric vehicle fleet, while maintaining a comparable level of deadhead kilometers from traditional vehicles.

Fleet	**1st**	**2nd**
Objective function value	146.28	106.28
Total Deadhead	161.73	177.32
Charging	[]	[]
SoC	[229.0, 1.695, 1.695]	[229.0, 0.19, 0.19, 229.0, 0.30, 0.30]
Kilometers by EVs	110.07	119.21
Kilometers by TVs	51.66	58.10
Time[seconds]	2.3496	600
Costs		
Depot-to-trip	17.8%	12.5%
Trip-to-trip	49.2%	74.2%
Trip-to-Depot	33%	13.4%

Table 5.7: Results of Line 70 and 73

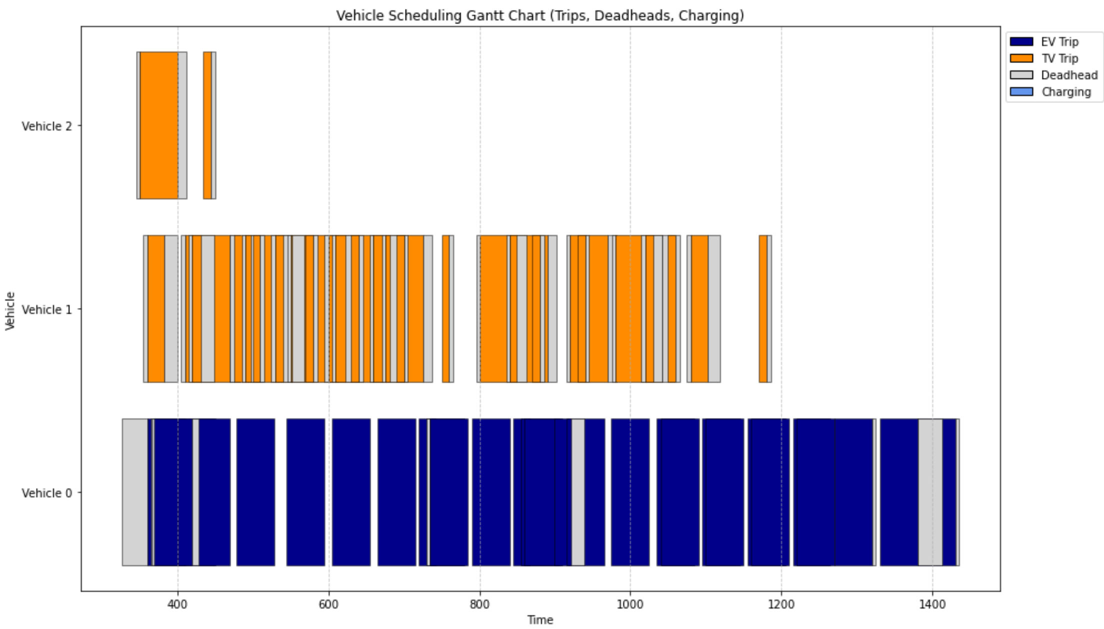

Figure 5.25: Gantt Lines 70 and 73, Case 1

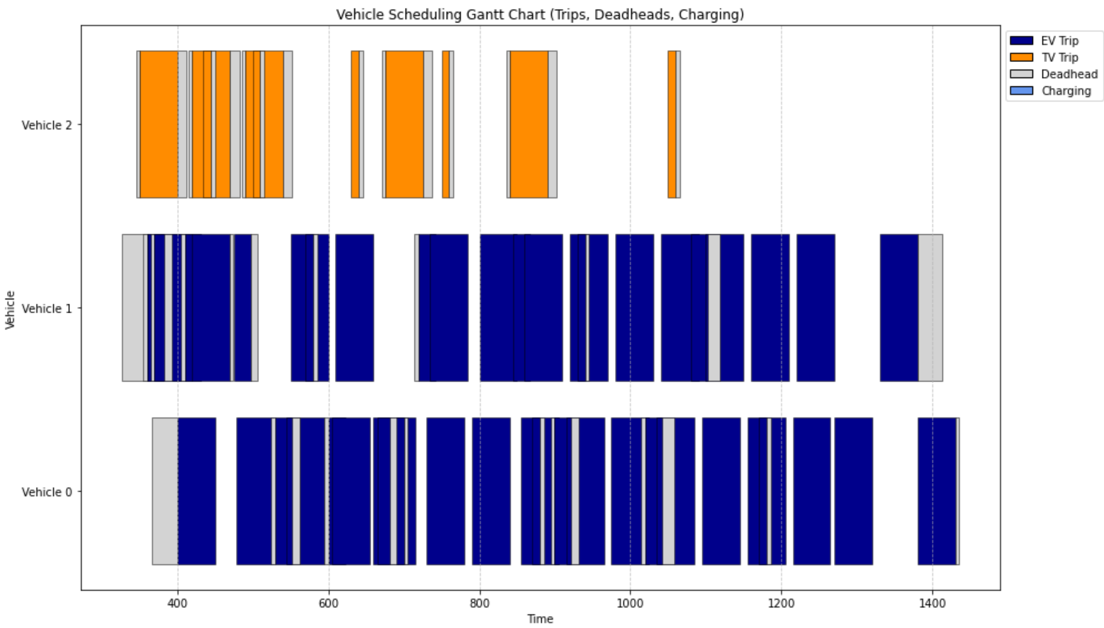

Figure 5.26: Gantt Lines 70 and 73, Case 2

Chapter 6

Conclusion

Effectively addresses the high complexity of detailed temporal tracking for batteries, the model Mixed-Fleet Electric Vehicle Scheduling Problem (MF-(E)VSP by Cycle model aims to generated a segment of the solution successfully. The model's approach enables to track the battery levels, consumption and charging within the design periods, creating simple generations.

The application of the MF-(E)VSP by Cycle in the generated scenarios with small-medium sized cities results into a trackable performance and operational decisions upon the selection of electric vehicles and traditional vehicles for complete the timetable design. An analysis about the results is that even if the costs per kilometer for electric vehicles is lower in comparative with traditional vehicles, not in all the cases is selected the only use of electric vehicles considering large distance between the trips points and the depots. This relation highlight the dependence of the city features for decide between charging or use expensive vehicles. Considering the both type of vehicles is possible to generated solutions more affordable for cities. The diversification of energy sources strategy for reduce the emissions without the absolute transition to one energy source technology; partial conversions are shown to be a viable and effective strategy for cities for reach sustainability program. The incentives observed demonstrated scenarios where in-period charging was highly advantageous.

The results for a real mixed city, Torino, demonstrate the complementarity achieved by utilizing both vehicle source types. Furthermore, they highlight the importance of considering line characteristics and distances to determine the most convenient distribution of trips and the minimal requirements for their completion. Given the operational costs per kilometer in 2024, the current lines support the possibility of reduced operational costs, even with a non-fully electric fleet. There is a tendency for electric vehicles to utilize all available energy, even if this increases deadhead kilometers. This phenomenon indicates that the price difference between energy sources incentivizes the maximization of electric vehicle use, specifically by assigning them paths that allow them to complete a higher number of trips.

Furthermore, this research identify crucial points to be worked in the future, as the integration of parallel charging capabilities. The current model only stipulates a limit of charging in the general period, the strong detail of a two or more vehicles using an specific charger at an determinate point of time is not integrated. The development in this point is crucial for generate solutions given the capacities of charging for each depot. For the present cases, is considered the minimum use through the cases that don't considerate an incentive for charging the vehicles and a extreme point for a reduction of cost for charge activities during a period. This definitions considered extreme cases about charging decisions without higher detail information about the time of use of each technology. Nerveless, is considered for the trips sequence for the vehicles the time used for charge. A possible solution for incorporate the MF-(E)VSP is the utilization of a second phase that check and guarantees through constraints aggregation to the model the double use of chargers at the same time.

The tests are delimitated for small-medium cities. For applications larger cities sizes the use of a pre phase or heuristic that simplified the information considerate for the model is a potentially propose, considering that some trip contains similar initial and end points, is possible for determinate some facilities for introduce the MF-(E)VSP into large cities sizes, making the model scalable.

Finally, the results demonstrated that the solutions for the programming implementation of the MF-(E)VSP find feasible and optimized solutions. The Mixed-fleet model considerate effectually cases of difference features of vehicles, including battery characteristics and energy sources. Due the analysis of results the model perceives a relation to cities prices energy contracts definitions and operational requirements.

Appendix A

Appendix

A.1 Python Program

1. Libraries and Creation of the Model

```
import pyomo.environ as pyo
from pyomo.opt import SolverStatus, TerminationCondition
import random
import time

# Creating the model
model = pyo.ConcreteModel()
```

Listing A.1: Imports and Model Initialization

2. Sets of the Model

```
# Sets of the model
rlarge = [0,1,2]
model.r = pyo.Set(initialize=rlarge)
lens = 160
listas = []
for i in range(lens):
    listas.append(i)
model.s = pyo.Set(initialize=listas)

model.u = pyo.Set(initialize=[0,1,2]) #Set of type of vehicles

lenq = 3
listaq = []
```

```
    for i in range(lenq):
        listaq.append(i)

    model.q = pyo.Set(initialize=listaq) #Set of depots

    plarge = [0,1,2,3,4,5,6]
    model.p = pyo.Set(initialize=plarge) #Set of chargers in the depot

    # EV and Traditional Vehicle (TV) types
    type1 = [0,1,2]
    type2 = [3,4]
    type3 = [5,6,7]

    theta = []
    for i in type1:
        theta.append(165/80/104)
    for i in type2:
        theta.append(165/80/104)

    model.k = pyo.Param(model.u,initialize={0:type1,1:type2,2:type3})
    listke = []
    for i in type1:
        listke.append(i)
    for i in type2:
        listke.append(i)

    model.ke = pyo.Set(initialize=listke) # Vehiculos electricos
    model.kt = pyo.Set(initialize=type3) # Vehiculos tradicionales
    model.typee = pyo.Set(initialize= [0,1])

    list = []
    for aux in model.u:
        for i in range (len(model.k[aux])):
            auxi = model.k[aux]
            list.append(auxi[i])

    model.ku = pyo.Set(initialize=list)
```

Listing A.2: Sets of the Model

3. Parameters of the Model

```
# Params of the model
Du = [42,104,298]
Dreal = []
for i in type1:
    Dreal.append(Du[1])
for i in type2:
    Dreal.append(Du[2])

listD = {key: Dreal[key] for key in model.ke}
model.D = pyo.Param(model.ke, initialize=listD) # Kilometers

listcq = {(0,0):2,(0,1):2,(0,2):0,(1,0):0,(1,1):2,(1,2):1,\\
 (2,0):2,(2,1):1,(2,2):4}
model.cq = pyo.Param(model.q,model.u, initialize=listcq) # Number of vehicles admited at the depot

endtimelist = {key: int(random.uniform(332,1012)) for key in listas}
startimelist = {key: key+int(random.uniform(10,30)) for key in endtimelist}
model.endtime = pyo.Param(model.s, initialize=endtimelist)
model.startime = pyo.Param(model.s, initialize=startimelist)

dijmum = {(key,cey): int(random.uniform(0,3)) for key in listas for cey in listas}
model.dij = pyo.Param(model.s,model.s, initialize=dijmum)
dhtijmum = {(key,cey): (20/60)*dijmum[key,cey] for key in listas for cey in listas}
model.dhtij = pyo.Param(model.s,model.s, initialize=dhtijmum)

dhiqmum = {(key,cey): int(random.uniform(2, 5)) for key in listas for cey in listaq}
model.dhiq = pyo.Param(model.s,model.q, initialize=dhiqmum)
dhqimum = {(key,cey): int(random.uniform(2, 5)) for key in listaq for cey in listas}
```

```
    model.dhqi = pyo.Param(model.q,model.s, initialize=dhqimum)

    listprice = []
    for ke in type1:
        listprice.append(0.2072) # EUR/km; 0.216 EUR/kWh
    for ke in type2:
        listprice.append(0.2246) # EUR/km; 0.216 EUR/kWh
    for kt in model.kt:
        listprice.append(0.69) # EUR/km; 1.232 EUR/l

    cu = {key: listprice[key] for key in model.ku}
    model.cu = pyo.Param(model.ku, initialize=cu)

    listli = {key: int(random.uniform(10,60)) for key in model.s}
    model.li = pyo.Param(model.s, initialize=listli)
```

Listing A.3: Parameters of the Model

4. Variables of the Model

```
    model.x = pyo.Var(model.r,model.s,model.s,model.ku,
    within=pyo.Binary) # Travel between i and j
    model.xa = pyo.Var(model.r,model.q, model.s, model.ku, within=pyo.Binary) # Travel from depot to trip start
    model.xb = pyo.Var(model.r,model.s, model.q, model.ku, within=pyo.Binary) # Travel from trip end to depot
    model.xc = pyo.Var(model.r,model.q, model.p, model.ku, within=pyo.Binary) # Charging path
    model.Start = pyo.Var(model.q, model.ku, within=pyo.Binary) # Vehicle start from depot
    model.End = pyo.Var(model.q, model.ku, within=pyo.Binary) # Vehicle end at depot

    listSoC_init = {}
    for k_val in model.ke:
        listSoC_init[(0, k_val)] = model.D[k_val] # Initial SoC at the start of period 0

    model.SoC = pyo.Var(model.r, model.ke, initialize=listSoC_init, bounds=(0.0, None))
    listCh = {(key,cey): 0 for key in model.r for cey in model.ke}
```

```
 model.Ch = pyo.Var(model.r, model.ke, initialize=listCh, bounds=(0.0, None)) # Charge realized at the end of period r
```

Listing A.4: Variables of the Model

5. Objective Function

```
 model.obj = pyo.Objective(expr=sum(sum(sum(model.x[r,i,j,ku]\\
 *model.cu[ku]*model.li[i] for i in model.s for j in model.s if i\neq j)for ku in model.ku) for r in model.r)+sum(sum(sum(sum(model.xa[r,q,i,ku]*model.cu[ku]\\
 *model.dhqi[q,i] for q in model.q)for i in model.s)for ku in model.ku)for r in model.r)+sum(sum(sum(sum(model.xb[r,i,q,ku]*model.cu[ku]\\
 *model.dhiq[i,q] for i in model.s)for q in model.q)for ku in model.ku) for r in model.r), sense=pyo.minimize)
```

Listing A.5: Objective Function

6. Constraints

```
 # 2. Constraint: Each Trip is run by just one vehicle, flow.6in
 def flow_in(model,j):
     return sum(sum(sum(model.x[r,i,j,ku] for i in model.s if i\neq j) + sum(model.xa[r,q,j,ku] for q in model.q) for ku in model.ku) for r in model.r) = 1
 model.cons1 = pyo.Constraint(model.s,rule=flow_in)

 # 3. Constraint: Each Trip is run by just one vehicle, flow.6out
 def flow_out(model, i):
  return sum(sum(sum(model.x[r,i,j,ku] for j in model.s if j \neq i) + sum(model.xb[r,i,q,ku] for q in model.q) for ku in model.ku) for r in model.r) .6=1
 model.cons2 = pyo.Constraint(model.s,rule=flow_out)

 # 4. Constraint: Connection between trips
 def conn(model,r,i,j,ku):
 if (model.endtime[i] < model.startime[j]) and (i \neq j):
     return model.endtime[i] + model.dhtij[i,j]*model.x[r,i,j,ku] \leq model.startime[j]
```

```
    else:
        return model.x[r,i,j,ku] = 0
    model.cons3 = pyo.Constraint(model.r,model.s,model.s,model.ku, rule=conn)

    # 5. Constraint: Depot assignation
    def assign(model,q,ku):
        return model.Start[q,ku] = model.End[q,ku]
    model.cons4 = pyo.Constraint(model.q,model.ku,rule=assign)

    def starter(model,r,q,k,i):
        return model.xa[r,q,i,k] \leq model.Start[q,k]
    model.cons5 = pyo.Constraint(model.r,model.q,model.ku,model.s, rule=starter)

    def ending(model,q,k):
        return model.End[q,k]\leq sum(sum(model.xb[r,i,q,k] for i in model.s)for r in model.r)
    model.cons13 = pyo.Constraint(model.q,model.ku, rule=ending)

    def unique(model,k):
        return sum(model.Start[q,k] for q in model.q) \leq 1
    model.cons21 = pyo.Constraint(model.ku, rule=unique)

    def flow(model,q,k,r):
        return sum(model.xa[r,q,i,k] for i in model.s) = sum(model.xb[r,i,q,k] for i in model.s)
    model.cons14 = pyo.Constraint(model.q,model.ku,model.r,rule=flow)

    # 6. Depot Capacity
    def cap(model,q):
        return sum(model.Start[q,k] for k in model.ku) = sum(model.End[q,k] for k in model.ku)
    model.cons6 = pyo.Constraint(model.q, rule=cap)

    # 7. Depot Capacity electric vehicles
    def capev(model,q):
        return sum(model.Start[q,k] for k in model.ke) \leq model.cq[q,0]
    model.cons22 = pyo.Constraint(model.q, rule=capev)
```

```

    def captv(model,q):
        return sum(model.Start[q,k] for k in model.kt) \leq model.cq[q,1]
    model.cons23 = pyo.Constraint(model.q, rule=captv)

    def capa(model,q):
        return sum(model.End[q,k] for k in model.ku) \leq sum(model.cq[q,typee] for typee in model.typee)
    model.cons7 = pyo.Constraint(model.q, rule=capa)

    # 9. Constraint: Battery Energy
    def SoCcon(model, r,k):
        if 1\leq r\leqlen(rlarge):
            return model.SoC[r,k] = model.SoC[r.61,k] + model.Ch[r,k] .6 sum(sum(model.x[r.61,i,j,k]*model.li[i] for i in model.s) for j in model.s).6 sum(sum(model.xa[r.61,q,i,k]*model.dhqi[q,i] for q in model.q) for i in model.s).6 sum(sum(model.xb[r.61,i,q,k]*model.dhiq[i,q] for i in model.s) for q in model.q)
         else:
            return model.SoC[r,k] = model.D[k]
    model.cons8 = pyo.Constraint(model.r,model.ke, rule=SoCcon)

    def chargech(model,r,k):
        return model.D[k]*sum(model.xc[r,q,p,k] for q in model.q for p in model.p)\geq model.Ch[r,k]
    model.cons25 = pyo.Constraint(model.r,model.ke, rule=chargech)

    # 10. Constraint: Available energy for charge
    def Avcharge(model,r,k):
        if 1\leq r \leqlen(rlarge):
            return sum(sum(model.Ch[r,k] for q in model.q) for p in model.p) \leq model.D[k] .6 model.SoC[r.61,k]
        else:
            return 0 \leq model.Ch[r,k]
    model.cons10 = pyo.Constraint(model.r,model.ke,rule=Avcharge)

    # 11. Constraint: Minimum level of battery
    def minSoC(model,r,k):
        return 0 \leq model.SoC[r,k]
```

```
    model.cons11 =
pyo.Constraint(model.r,model.ke,rule=minSoC)

    # 12. Constraint: One charge at time
    def nondue(model,r,ku):
        return sum(sum(model.xc[r,q,p,ku] for p in model.p)
for q in model.q) \leq 1
    model.cons19 = pyo.Constraint(model.r,model.ke,
rule=nondue)

    # Flow in point function
    def neo(model, r, i, ku):
        return sum(model.x[r,j,i,ku] for j in model.s) +
sum(model.xa[r,q,i,ku] for q in model.q) =
sum(model.x[r,i,j,ku] for j in model.s) +
sum(model.xb[r,i,q,ku] for q in model.q)
    model.cons20 = pyo.Constraint(model.r,model.s,model.ku,
rule=neo)

    # Time stroke
    def stroke(model, r, ku):
        return sum(sum(model.xa[r,q,i,ku]*model.startime[i]
for i in model.s) for q in model.q) \leq
sum(sum(model.x[r,i,j,ku]*((model.li[i]*60/20)+
        (model.dhtij[i,j])) for i in model.s) +
sum(model.xa[r,q,j,ku]*((model.dhqi[q,j]*60/20)+
        model.startime[j]) for q in model.q) for j in
model.s)
    model.cons15 = pyo.Constraint(model.r,model.ku,
rule=stroke)

    def rock(model, r, ku):
        return
sum(sum(model.x[r,i,j,ku]*((model.li[i]*60/20)+
        (model.dhtij[i,j])) for i in model.s) +
sum(model.xa[r,q,j,ku]*((model.dhqi[q,i]*60/20)
        +model.startime[j]) for q in model.q) for j in
model.s) \leq
sum(sum(model.xb[r,i,q,ku]*model.endtime[i] for i in
model.s) for q in model.q)
    model.cons16 = pyo.Constraint(model.r,model.ku,
rule=rock)

    def tradition(model,ku):
```

```
        return sum(sum(sum(model.x[r,i,j,ku]*(model.li[i] +
model.dij[i,j]) for i in model.s )for j in model.s) +
sum(sum(model.xa[r,q,i,ku]*(model.dhqi[q,i]) for q in
model.q)    for i in model.s)+
sum(sum(model.xb[r,i,q,ku]*(model.li[i]+model.dhiq[i,q])
for i in model.s) for q in model.q) for r in model.r)
\leq 242
    model.cons24 = pyo.Constraint(model.kt, rule=tradition)

    def after(model,r,l,q,ku):
    if r>l:
        if (r\neq 0):
            if ku in model.ke:
                return
10000000000*(1.6sum(model.xa[r,q,i,ku] for i in model.s))
+ sum(model.xa[r,q,i,ku]*model.startime[i] for i in
model.s) \gec sum(model.xb[l,i,q,ku]*model.endtime[i]
for i in model.s) + sum(model.Ch[l,ku]*60*(theta[ku])
for p in model.p)
            else:
                return
10000000000*(1.6sum(model.xa[r,q,i,ku] for i in model.s))
+ sum(model.xa[r,q,i,ku]*model.startime[i] for i in
model.s) \geq sum(model.xb[l,i,q,ku]*model.endtime[i]
for i in model.s)
        else:
            return 0 \gec sum(model.xa[r,q,i,ku] for i in
model.s)
    else:
        return 0 \geq sum(model.xa[r,q,i,ku] for i in
model.s)
    model.cons18 =
pyo.Constraint(model.r,model.r,model.q,model.ku,
rule=after)

    def coli(model,k,r):
        return
sum(model.xa[r,q,i,k]*(model.li[i]+model.dhqi[q,i]) for
q in model.q for i in model.s) +
sum(model.x[r,i,j,k]*(model.dij[i,j] + model.li[j]) for
i in model.s for j in model.s)+
sum(model.xb[r,i,q,k]*(model.dhiq[i,q]) for i in model.s
for q in model.q) \leq model.D[k]
    cons34 = pyo.Constraint(model.ke,model.r, rule=coli)
```

Listing A.6: Constraints

7. Solver Configuration and Execution

```
# Solver
solver = pyo.SolverFactory('gurobi')

start_time = time.time()

# Results
result = solver.solve(model, tee=True)

end_time = time.time()
total_solve_duration = end_time .6 start_time
```

Listing A.7: Solver Configuration and Execution

A.2 Generation of cases

For the generation of cases, the references for each city domain values are define in the Table A.1.

A.3 Results of Tests

The values results of the programming application are characterized for the following points.

Objective Function Value: The value of the objective function observe by each test realized, the measure EUR and considerate the kilometers with-out passenger during the period.

DH (Deadhead Kilometers): Kilometers of driving without passengers, this item considerate the sum of all the vehicles used.

Ch (Charge Actions), SoC (State of Charge): The list of changes of battery are measure in two areas, the level of energy of each electric vehicle and also the decision of charger the vehicle. The both are counted in kilometers available for the vehicle for simplified the writing.

Km EV (Electric Vehicle Kilometers): For track the decision of the model to use a electric vehicle, and given the objective function description is used the number of kilometers related to this type of vehicles.

Symbol	**C1**	**C2, C3, C5**	**C4**
s_i	random[332,1012]	random[332,1012]	random[332,1012]
e_i	s_i+ random[10,60]	s_i+ random[10,60]	s_i+ random[10,60]
l_i	random[2,20]	random[4,25]	random[5,20]
l_{qi}	random[2,10]	random[2,10]	random[2,10]
l_{iq}	random[2,10]	random[2,10]	random[2,10]
t_{ij}	$(20/60) * l_{ij}$	$(20/60) * l_{ij}$	$(20/60) * l_{ij}$
Symbol	**C6**	**C7, C8, C9**	**C10, C11, C12, C14, C15, C16, C17, C18, C19, C20**
s_i	random[332,1012]	random[332,1012]	random[332,1012]
e_i	s_i+ random[10,60]	s_i+ random[10,30]	s_i+ random[10,30]
l_i	random[4,19]	random[6,18]	random[10,30]
l_{qi}	random[2,10]	random[2,10]	random[2,5]
l_{iq}	random[2,10]	random[2,10]	random[2,5]
l_{ij}	[2,3]	[2,3]	random[0,5]
t_{ij}	$(20/60) * l_{ij}$	$(20/60) * l_{ij}$	$(20/60) * l_{ij}$
Symbol	**C13**		
s_i	random[332,1012]		
e_i	s_i+ random[10,30]		
l_i	random[10,60]		
l_{qi}	random[2,5]		
l_{iq}	random[2,5]		
l_{ij}	random[0,3]		
t_{ij}	$(20/60) * l_{ij}$		

Table A.1: Random values per Case

Km TV (Traditional Vehicle Kilometers): The number of kilometers deadhead selected for the model decisions allow understand the inclusion of this vehicles into the city for complete the timetable.

Total Solve Duration (s): For considerate how much time is necessary for find a solution is considered the time searching using by the solver.

Table A.2: Optimization Results for C1 Scenarios

Metric	C1T1	C1T2	C1T3	C1T4	C1T5	C1T6	C1T7	C1T8	C1T9	C1T10
Objective Function Value	81.6368	44.3408	46.8272	34.2718	40.7124	37.5870	45.5840	38.2260	37.4241	36.9828
DH (Km)	754.0000	765.0000	792.0000	772.0000	809.0000	792.0000	789.0000	784.0000	813.0000	814.0000
Ch	[]	[]	[]	[19.0, 19.0]	[18.0, 18.0]	[19.0, 19.0]	[]	[4.0, 18.0, 18.0]	[21.0]	[18.0, 18.0]
SoC	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 19.0, 298.0, 0.0, 19.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 298.0, -0.0, 18.0, 298.0, -0.0, 18.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 19.0, 298.0, 0.0, 19.0]	[104.0, 104.0, 104.0, 104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 298.0, -0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, 0.0, 4.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 18.0, 298.0, -0.0, 18.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.0, 298.0, 0.0, 0.0]	[104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 18.0, 298.0, -0.0, 18.0]
Km EV	506.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000
Km TV	248.0000	65.0000	92.0000	72.0000	109.0000	92.0000	89.0000	84.0000	113.0000	114.0000
Total Solve Duration (s)	62.9405	54.7563	62.8950	58.6481	71.0907	48.3442	72.0691	62.4084	52.5114	50.0767

Table A.3: Optimization Results for C2 Scenarios

Metric	C2T1	C2T2	C2T3	C2T4	C2T5	C2T6	C2T7	C2T8	C2T9	C2T10
Objective Function Value	62.4291	68.8500	62.7044	61.5655	65.4343	62.2900	62.4988	65.9880	64.6056	63.3972
DH (Km)	605.0000	608.0000	588.0000	609.0000	540.0000	619.0000	624.0000	624.0000	637.0000	582.0000
Ch	[]	[]	[]	[]	[]	[]	[]	[]	[]	[]
SoC	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]
Km EV	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000
Km TV	355.0000	358.0000	338.0000	359.0000	290.0000	369.0000	374.0000	374.0000	387.0000	332.0000
Total Solve Duration (s)	21.9832	23.6784	20.8242	18.8844	17.7856	19.1430	21.5824	18.9530	19.2360	20.3217

Table A.4: Optimization Results for C3 Scenarios

Metric	C3T1	C3T2	C3T3	C3T4	C3T5	C3T6	C3T7	C3T8	C3T9	C3T10
Objective Function Value	62.9131	61.8407	63.2927	62.7392	59.9427	65.9184	63.6028	65.3996	67.6804	63.2231
DH (Km)	355.0000	438.0000	346.0000	349.0000	335.0000	360.0000	381.0000	394.0000	368.0000	363.0000
Ch	[]	[]	[]	[]	[]	[]	[]	[]	[]	[]
SoC	[42.0, -0.0, 0.0, 0.0, 0.0, 104.0, 0.0, 0.0, 0.0, 0.0, 104.0, -0.0, 0.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, -0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, -0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, 0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, 0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, -0.0, 0.0, 42.0, 42.0, 42.0, 104.0, 0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, -0.0, 0.0, 42.0, 42.0, 42.0, 104.0, -0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, 42.0, 42.0, 42.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0]
Km EV	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000	250.0000
Km TV	105.0000	105.0000	96.0000	99.0000	85.0000	110.0000	131.0000	144.0000	118.0000	113.0000
Total Solve Duration (s)	5.6464	4.7789	5.3134	5.2059	5.3730	6.3578	6.1606	5.0146	6.1306	5.3264

Table A.5: Optimization Results for C4 Scenarios

Metric	C4T1	C4T2	C4T3	C4T4	C4T5	C4T6	C4T7	C4T8	C4T9	C4T10
Objective Function Value	318.0688	324.5103	307.3339	292.3563	320.9255	332.4915	317.8743	322.4913	293.5643	305.1991
DH (Km)	500.0000	527.0000	492.0000	482.0000	517.0000	507.0000	496.0000	514.0000	501.0000	499.0000
Ch	[]	[]	[]	[]	[298.0]	[]	[]	[]	[]	[]
SoC	[104.0, 0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, -0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, -0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, -0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, -0.0, 0.0, 298.0, 0.0, 298.0]	[104.0, -0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, 0.0, 0.0, 298.0, 1.0, 1.0]	[104.0, -0.0, 0.0, 298.0, -0.0, 0.0]	[104.0, -0.0, 0.0, 298.0, -0.0, 0.0]
Km EV	402.0000	402.0000	402.0000	402.0000	402.0000	402.0000	402.0000	401.0000	402.0000	402.0000
Km TV	98.0000	125.0000	90.0000	80.0000	115.0000	105.0000	94.0000	113.0000	99.0000	97.0000
Total Solve Duration (s)	1.2880	1.7455	1.4036	1.4073	1.4889	1.4455	1.7180	1.6434	1.8354	1.6901

Table A.6: Optimization Results for C5 Scenarios

Metric	C5T1	C5T2	C5T3	C5T4	C5T5	C5T6	C5T7	C5T8	C5T9	C5T10
Objective Function Value	225.5099	219.3323	219.3367	233.0720	214.4047	216.8871	203.9159	279.3281	298.3987	163.7827
DH (Km)	265.0000	262.0000	259.0000	263.0000	258.0000	258.0000	250.0000	430.0000	252.0000	256.0000
Ch	[104.0]	[42.0]	N/A	N/A	N/A	N/A	N/A	N/A	[42.0]	N/A
SoC	[42.0, -0.0, 0.0, 104.0, -0.0, 104.0]	[42.0, 0.0, 42.0, 104.0, -0.0, 0.0]	[42.0, -0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, -0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, -0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, -0.0, 0.0, 104.0, -0.0, 0.0]	[42.0, 0.0, 0.0, 104.0, 0.0, 0.0]	[42.0, -0.0, 42.0, 104.0, -0.0, 0.0]	[42.0, -0.0, 0.0, 104.0, -0.0, 0.0]
Km EV	146.0000	146.0000	146.0000	146.0000	146.0000	146.0000	146.0000	146.0000	146.0000	146.0000
Km TV	119.0000	116.0000	113.0000	117.0000	112.0000	112.0000	104.0000	284.0000	106.0000	110.0000
Total Solve Duration (s)	1.3145	1.2027	1.1867	1.3757	1.2278	1.5468	1.8998	11.3825	1.3582	1.2818

Table A.7: Optimization Results for C6 Scenarios

Metric	C6T1	C6T2	C6T3	C6T4	C6T5	C6T6	C6T7	C6T8	C6T9	C6T10
Objective Function Value	117.7396	119.7950	117.7820	118.7850	119.8464	118.7850	116.9854	22.2143	23.1429	163.7827
DH (Km)	417.0000	422.0000	405.0000	406.0000	409.0000	406.0000	414.0000	418.0000	404.0000	409.0000
Ch	[104.0, 104.0, 7.43, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 20.93]	[104.0, 104.0, 7.43, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.0]	[104.0, 104.0, 7.43, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.14]	[104.0, 104.0, 7.43, 298.0, 21.21]
SoC	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 5.0, 25.93]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 0.0, 21.29]	[104.0, 0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 4.0, 25.0]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, 2.0, 23.14]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 1.0, 22.21]
Km EV	401.0000	401.0000	397.0000	402.0000	401.0000	402.0000	398.0000	401.0000	400.0000	401.0000
Km TV	16.0000	21.0000	8.0000	4.0000	8.0000	4.0000	16.0000	17.0000	4.0000	8.0000
Total Solve Duration (s)	4.0319	4.1305	3.0923	2.8564	3.4355	2.8564	3.4235	3.9182	3.2934	3.2480

Table A.8: Optimization Results for C7 Scenarios

Metric	C7T1	C7T2	C7T3	C7T4	C7T5	C7T6	C7T7	C7T8	C7T9	C7T10
Objective Function Value	116.0711	117.1325	118.3917	121.8930	117.2208	118.1192	116.8412	122.1524	116.3572	117.2556
DH (Km)	417.0000	420.0000	409.0000	421.0000	424.0000	418.0000	422.0000	420.0000	423.0000	417.0000
Ch	[104.0, 7.43, 104.0, 298.0, 21.14]	[104.0, 7.43, 104.0, 298.0, 21.07]	[104.0, 7.43, 104.0, 298.0, 20.93]	[104.0, 104.0, 7.43, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.21]	[104.0, 7.43, 104.0, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.29]	[104.0, 104.0, 7.43, 298.0, 21.21]	[104.0, 104.0, 7.43, 298.0, 21.21]
SoC	[104.0, 0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 2.0, 23.14]	[104.0, 0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 3.0, 24.07]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 5.0, 25.93]	[104.0, 104.0, 104.0, 104.0, -0.0, 0.43, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21]	[104.0, 0.0, 7.43, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, -0.0, 0.43, 298.0, -0.0, 14.29]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, 1.0, 22.21]
Km EV	400.0000	399.0000	397.0000	409.0000	401.0000	401.0000	401.0000	416.0000	401.0000	401.0000
Km TV	17.0000	21.0000	12.0000	12.0000	23.0000	17.0000	21.0000	4.0000	22.0000	16.0000
Total Solve Duration (s)	2.1743	1.9021	1.7646	1.9454	2.1920	1.7581	1.8705	1.7314	1.6504	1.4862

Table A.9: Optimization Results for C8 Scenarios

Metric	C8T1	C8T2	C8T3	C8T4	C8T5	C8T6	C8T7	C8T8	C8T9	C8T10
Objective Function Value	84.4160	82.2396	77.5040	80.7528	87.1776	87.8008	76.1912	86.2444	79.0604	83.6536
DH (Km)	749.0000	776.0000	779.0000	798.0000	753.0000	767.0000	819.0000	771.0000	782.0000	759.0000
Ch	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 7.43, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 7.43, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 7.43, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 7.43, 298.0, 21.29, 298.0, 21.29]
SoC	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, -0.0, 7.43, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, -0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 0.0, 7.43, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 0.0, 7.43, 298.0, 0.0, 21.29, 298.0, -0.0, 21.29]
Km EV	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000	700.0000
Km TV	49.0000	76.0000	79.0000	98.0000	53.0000	67.0000	119.0000	71.0000	82.0000	59.0000
Total Solve Duration (s)	17.3586	24.1892	15.3682	20.6293	14.5847	18.2538	37.4414	17.0484	20.0919	18.0073

Table A.10: Optimization Results for C9 Scenarios

Metric	C9T1	C9T2	C9T3	C9T4	C9T5	C9T6	C9T7	C9T8	C9T9	C9T10
Objective Function Value	41.0504	43.2964	42.3980	39.9354	44.6440	44.6440	43.2964	44.1948	44.6440	42.6306
DH (Km)	632.0000	635.0000	627.0000	639.0000	651.0000	661.0000	642.0000	657.0000	649.0000	621.0000
Ch	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.21, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.21, 298.0, 21.29]
SoC	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 13.29, 298.0, -0.0, 13.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21, 298.0, -0.0, 21.29]
Km EV	596.0000	612.0000	596.0000	595.0000	612.0000	612.0000	612.0000	612.0000	612.0000	595.0000
Km TV	36.0000	23.0000	31.0000	44.0000	39.0000	49.0000	30.0000	45.0000	37.0000	26.0000
Total Solve Duration (s)	5.0291	4.4233	4.3485	5.3629	4.3101	4.4459	4.1216	4.8562	4.7728	4.5816

Table A.11: Optimization Results for C10 Scenarios

Metric	C10T1	C10T2	C10T3	C10T4	C10T5	C10T6	C10T7	C10T8	C10T9	C10T10
Objective Function Value	306.1548	309.0120	321.6404	325.6346	333.9632	302.3690	345.0032	327.0956	315.8310	321.1264
DH (Km)	625.0000	629.0000	638.0000	636.0000	644.0000	624.0000	652.0000	640.0000	631.0000	634.0000
Ch	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.21, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.21]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.14]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.21]	[104.0, 104.0, 298.0, 21.29, 298.0, 21.29]
SoC	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, -0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 1.0, 22.21, 298.0, 0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 21.29, 298.0, 2.0, 23.14]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 0.0, 21.29]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, 1.0, 22.21]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 21.29, 298.0, -0.0, 21.29]
Km EV	596.0000	596.0000	596.0000	595.0000	596.0000	595.0000	594.0000	596.0000	595.0000	596.0000
Km TV	29.0000	33.0000	42.0000	41.0000	48.0000	29.0000	58.0000	44.0000	36.0000	38.0000
Total Solve Duration (s)	5.6368	5.6833	6.4827	5.4067	5.1466	6.5065	5.7330	5.9667	5.5286	6.0243

Table A.12: Optimization Results for C11 Scenarios

Metric	C11T1	C11T2	C11T3	C11T4	C11T5	C11T6	C11T7	C11T8	C11T9	C11T10
Objective Function Value	504.0552	479.9052	492.9040	488.0092	458.8208	474.8668	444.8448	481.5260	493.1124	471.4816
DH (Km)	766.0000	749.0000	761.0000	752.0000	733.0000	741.0000	728.0000	750.0000	760.0000	738.0000
Ch	[20.0, 20.0]	[]	[20.0, 20.0]	[18.0, 16.0]	[19.0, 19.0]	[]	[19.0, 19.0]	[]		[17.0]
SoC	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 20.0, 298.0, -0.0, 20.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 20.0, 298.0, 0.0, 20.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 18.0, 298.0, -0.0, 16.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 19.0, 298.0, -0.0, 19.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 19.0, 298.0, -0.0, 19.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 104.0, 298.0, -0.0, 0.0, 298.0, -0.0, 17.0]
Km EV	596.0000	596.0000	596.0000	596.0000	596.0000	596.0000	596.0000	596.0000	596.0000	596.0000
Km TV	169.9999	153.0000	165.0000	156.0000	137.0000	145.0000	132.0000	154.0000	164.0000	142.0000
Total Solve Duration (s)	20.8050	34.2634	13.3109	14.8340	26.4210	30.8403	27.9018	36.4626	54.0277	24.8250

Table A.13: Optimization Results for C12 Scenarios

Metric	C12T1	C12T2	C12T3	C12T4	C12T5	C12T6	C12T7	C12T8	C12T9	C12T10
Objective Function Value	336.2256	340.6480	331.6482	327.8806	334.0492	327.5042	327.2954	320.0386	336.4344	338.5064
DH (Km)	760.0000	778.0000	757.0000	749.0000	750.0000	753.0000	753.0000	735.0000	762.0000	762.0000
Ch	[]	[]	[]	[]	[4.0]	[]	[]	[4.0]	[]	[]
SoC	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 298.0, 22.0, 22.0, 298.0, 22.0, 22.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 298.0, 17.0, 17.0, 298.0, 9.0, 9.0]	[104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 298.0, 36.0, 36.0, 298.0, 11.0, 11.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, -0.0, 0.0, 298.0, 2.0, 2.0, 298.0, 53.0, 53.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 298.0, 37.0, 37.0, 298.0, 17.0, 17.0]	[104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 298.0, 3.0, 3.0, 298.0, 48.0, 48.0]	[104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 298.0, 5.0, 5.0, 298.0, 46.0, 46.0]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 104.0, 0.0, 0.0, 298.0, 52.0, 52.0, 298.0, 17.0, 17.0]	[104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 298.0, 41.0, 41.0, 298.0, 1.0, 1.0]	[104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 298.0, 14.0, 14.0, 298.0, 28.0, 28.0]
Km EV	760.0000	778.0000	757.0000	749.0000	750.0000	753.0000	753.0000	735.0000	762.0000	762.0000
Km TV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Total Solve Duration (s)	54.2408	52.0867	54.9952	48.5027	61.2326	44.7003	47.3372	49.0802	48.5117	53.9231

Table A.14: Optimization Results for C13

Metric	C13T1	C13T2	C13T3	C13T4	C13T5	C13T6	C13T7	C13T8	C13T9	C13T10
Objective Function Value	251.35	250.32	251.62	251.27	251.27	251.78	250.77	251.78	251.78	250.77
DH	569	574	572	570	570	572	571	572	572	571
Ch	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 15.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.10, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.14, 298.0, 13.0]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]
SoC	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 15.0, 28.33, 298.0, 31.0, 43.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 44.0, 56.10, 298.0, 12.0, 25.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 43.0, 55.14, 298.0, 13.0, 26.0]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]
Km EV	569	574	572	570	570	572	571	572	572	571
Km TV	0	0	0	0	0	0	0	0	0	0
Total Solve Duration (s)	259.343	261.42	257.26	257.96	259.12	260.11	257.72	264.08	264.12	266.11

Table A.15: Optimization Results for C14

Metric	C14T1	C14T2	C14T3	C14T4	C14T5	C14T6	C14T7	C14T8	C14T9	C14T10
Objective Function Value	251.35	250.32	251.62	251.27	251.27	251.78	250.77	251.78	251.78	250.77
DH	569	574	572	570	570	572	571	572	572	571
Ch	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 15.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.10, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.14, 298.0, 13.0]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]
SoC	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 15.0, 28.33, 298.0, 31.0, 43.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 44.0, 56.10, 298.0, 12.0, 25.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 43.0, 55.14, 298.0, 13.0, 26.0]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]
Km EV	569	574	572	570	570	572	571	572	572	571
Km TV	0	0	0	0	0	0	0	0	0	0
Total Solve Duration (s)	299.05	287.41	273.66	228.64	293.38	276.59	228.39	263.58	302.97	244.60

Table A.16: Optimization Results for C15

Metric	C15T1	C15T2	C15T3	C15T4	C15T5	C15T6	C15T7	C15T8	C15T9	C15T10
Objective Function Value	462.0400	461.3920	468.4054	452.9380	458.8727	470.3778	458.4924	448.1282	469.4676	448.0664
DH (Km)	882.0000	879.0000	887.0000	873.0000	878.0000	885.0000	878.0000	866.0000	884.0000	873.0000
Ch	[2.0, 13.0, 13.0]	[4.0]	[4.0, 14.0]		[11.0, 11.0]	[10.0, 10.0]	[4.0, 10.0, 10.0]	[4.0, 4.0, 10.0, 10.0]	[10.0, 10.0]	[4.0, 11.0, 11.0]
SoC	[104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 298.0, -0.0, 12.0, 298.0, -0.0, 12.0]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 0.0, 4.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 104.0, 0.0, 0.0, 298.0, -0.0, 14.0, 298.0, 0.99, 0.99]	[104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 298.0, 0.0, 0.0, 298.0, 0.0, 0.0]	[104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 104.0, 0.0, 0.0, 298.0, -0.0, 11.0, 298.0, -0.0, 11.0]	[104.0, -0.0, 0.0, 104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 298.0, -0.0, 10.0, 298.0, 0.99, 10.99]	[104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 298.0, -0.0, 10.0, 298.0, -0.0, 10.0]	[104.0, 0.0, 4.0, 104.0, 0.0, 4.0, 104.0, 104.0, 104.0, 298.0, -0.0, 10.0, 298.0, 0.99, 10.99]	[104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 104.0, 0.0, 0.0, 298.0, -0.0, 10.0, 298.0, -0.0, 10.0]	[104.0, 0.0, 3.99, 104.0, 0.0, 0.0, 104.0, 104.0, 104.0, 298.0, -0.0, 11.0, 298.0, -0.0, 11.0]
Km EV	804	804	803	804	804	803	804	803	804	804
Km TV	78	75	84	69	74	82	74	63	80	69
Total Solve Duration (s)	331.2884	98.9936	319.4433	181.4591	274.3588	346.8913	395.4441	318.3735	320.3208	324.4024

Table A.17: Optimization Results for C16

Metric	C16T1	C16T2	C16T3	C16T4	C16T5	C16T6	C16T7	C16T8	C16T9	C16T10
Objective Function Value	457.35	257.37	246.84	251.82	258.35	255.24	251.82	257.94	259.51	255.46
DH	878	593	586	585	593	584	585	594	602	583
Ch	[4.0, 12.0, 12.0]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.95, 298.0, 13.38, 298.0]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.95, 298.0, 13.05, 298.0]	[104.0, 4.90, 104.0, 4.95, 104.0, 4.86, 298.0, 13.14, 298.0]	[104.0, 4.95, 104.0, 4.81, 104.0, 4.95, 298.0, 298.0, 13.52]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.95, 298.0, 298.0, 12.95]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.90, 298.0, 13.05, 298.0]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.95, 298.0, 13.43, 298.0]	[104.0, 4.95, 104.0, 4.90, 104.0, 4.95, 298.0, 298.0, 13.86]	[104.0, 4.95, 104.0, 4.95, 104.0, 4.95, 298.0, 12.90, 298.0]
SoC	[104.0, -0.0, 0.0, 104.0, 104.0, 104.0, 104.0, -0.0, 4.0, 298.0, -0.0, 12.0, 298.0, -0.0, 12.0]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 17.0, 30.38, 298.0, 298.0, 298.0]	[104.0, 0.0, 4.95, 104.0, 0.0, 4.95, 104.0, 0.0, 4.95, 298.0, 24.0, 37.05, 298.0, 298.0, 298.0]	[104.0, 1.0, 5.90, 104.0, 0.0, 4.95, 104.0, 2.0, 6.86, 298.0, 22.0, 35.14, 298.0, 298.0, 298.0]	[104.0, -0.0, 4.95, 104.0, 3.0, 7.81, 104.0, -0.0, 4.95, 298.0, 298.0, 298.0, 298.0, 14.0, 27.52]	[104.0, -0.0, 4.95, 104.0, 0.0, 4.95, 104.0, 0.0, 4.95, 298.0, 298.0, 298.0, 298.0, 26.0, 38.95]	[104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 1.0, 5.90, 298.0, 24.0, 37.05, 298.0, 298.0, 298.0]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 16.0, 29.43, 298.0, 298.0, 298.0]	[104.0, -0.0, 4.95, 104.0, 1.0, 5.90, 104.0, -0.0, 4.95, 298.0, 298.0, 298.0, 298.0, 7.0, 20.86]	[104.0, -0.0, 4.95, 104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 27.0, 39.90, 298.0, 298.0, 298.0]
Km EV	804	593	586	585	593	584	585	594	602	583
Km TV	74	0	0	0	0	0	0	0	0	0
Total Solve Duration (s)	322.33	12.41	15.92	14.59	13.61	14.65	14.43	14.12	15.24	13.23

Table A.18: Optimization Results for C17

Metric	C17T1	C17T2	C17T3	C17T4	C17T5	C17T6	C17T7	C17T8	C17T9	C17T10
Objective Function Value	282.19	281.23	281.11	286.36	284.26	286.23	279.37	279.89	281.51	284.02
DH	650	637	638	646	646	656	647	643	651	650
Ch	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 8.90, 298.0, 12.14]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 6.95, 298.0, 13.48]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 10.10, 298.0, 10.38]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 9.14, 298.0, 11.71]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 11.90, 298.0, 8.95]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 9.24, 298.0, 12.10]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 11.10, 298.0, 9.81]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 11.71, 298.0, 9.0]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 10.62, 298.0, 10.48]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 9.62, 298.0, 11.43]
SoC	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 111.0, 119.90, 298.0, 43.0, 55.14]	[104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 152.0, 158.95, 298.0, 15.0, 28.48]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 86.0, 96.10, 298.0, 80.0, 90.38]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 106.0, 115.14, 298.0, 52.0, 63.71]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 48.0, 59.90, 298.0, 110.0, 118.95]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 104.0, 113.24, 298.0, 44.0, 56.10]	[104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 65.0, 76.10, 298.0, 92.0, 101.81]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 52.0, 63.71, 298.0, 109.0, 118.0]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 75.0, 85.62, 298.0, 78.0, 88.48]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 96.0, 105.62, 298.0, 58.0, 69.43]
Km EV	650	637	638	646	646	656	647	643	651	650
Km TV	0	0	0	0	0	0	0	0	0	0
Total Solve Duration (s)	12.36	13.74	15.08	12.81	11.88	13.54	12.46	12.21	14.64	12.05

Table A.19: Optimization Results for C18

Metric	C18T1	C18T2	C18T3	C18T4	C18T5	C18T6	C18T7	C18T8	C18T9	C18T10
Objective Function Value	251.35	250.32	251.62	251.27	251.27	251.78	250.77	251.78	251.78	250.77
DH	569	574	572	570	570	572	571	572	572	571
Ch	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 15.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.10, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.14, 298.0, 13.0]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.24, 298.0, 12.43]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.14]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.05, 298.0, 13.05]
SoC	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 15.0, 28.33, 298.0, 31.0, 43.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 44.0, 56.10, 298.0, 12.0, 25.14]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 43.0, 55.14, 298.0, 13.0, 26.0]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 29.0, 42.24, 298.0, 37.0, 49.43]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 31.0, 44.14]	[104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 45.0, 57.05, 298.0, 32.0, 45.05]
Km EV	569	574	572	570	570	572	571	572	572	571
Km TV	0	0	0	0	0	0	0	0	0	0
Total Solve Duration (s)	12.02	12.44	12.55	12.43	13.12	12.29	12.59	12.64	12.61	12.42

Table A.20: Optimization Results for C19

Metric	C19T1	C19T2	C19T3	C19T4	C19T5	C19T6	C19T7	C19T8	C19T9	C19T10
Objective Function Value	332.3916	339.4744	334.4130	344.1404	336.1054	331.9266	337.4562	330.3038	339.1644	339.5598
DH (Km)	752.0000	770.0000	761.0000	796.0000	759.0000	761.0000	769.0000	765.0000	778.0000	765.0000
Ch	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 13.81, 298.0, 12.10]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 14.05, 298.0, 12.71]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 12.14, 298.0, 14.19]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.05, 298.0, 13.95]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 14.19, 298.0, 12.05]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 13.76, 298.0, 12.57]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 14.19, 298.0, 12.52]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 12.57, 298.0, 13.95]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 12.95, 298.0, 14.19]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 12.62, 298.0, 13.90]
SoC	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 8.0, 21.81, 298.0, 44.0, 56.10]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 3.0, 17.05, 298.0, 31.0, 43.71]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 43.0, 55.14, 298.0, -0.0, 14.19]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 3.0, 17.05, 298.0, 5.0, 18.95]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 0.0, 14.19, 298.0, 45.0, 57.05]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 298.0, 9.0, 22.76, 298.0, 34.0, 46.57]	[104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 0.0, 14.19, 298.0, 35.0, 47.52]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 34.0, 46.57, 298.0, 5.0, 18.95]	[104.0, 104.0, 104.0, 104.0, 0.0, 4.95, 104.0, 0.0, 4.95, 298.0, 26.0, 38.95, 298.0, -0.0, 14.19]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 33.0, 45.62, 298.0, 6.0, 19.90]
Km EV	752.0000	770.0000	761.0000	796.0000	759.0000	761.0000	769.0000	765.0000	778.0000	765.0000
Km TV	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Total Solve Duration (s)	18.8936	17.0315	18.2619	15.3235	15.8543	16.2720	16.0199	17.1109	15.3057	17.6801

Table A.21: Optimization Results for C20

Metric	C20T1	C20T2	C20T3	C20T4	C20T5	C20T6	C20T7	C20T8	C20T9	C20T10
Objective Function Value	364.7274	349.9800	371.4876	375.1696	360.1628	351.3276	363.7310	373.7240	359.9572	350.8088
DH (Km)	815.0000	804.0000	812.0000	820.0000	806.0000	804.0000	809.0000	814.0000	804.0000	804.0000
Ch	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 14.19, 298.0, 14.14]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 14.19, 298.0, 14.19]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.19, 298.0, 14.19]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 14.19, 298.0, 14.19]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.14, 298.0, 14.14]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.19, 298.0, 14.19]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.10, 298.0, 14.14]	[104.0, 4.95, 104.0, 4.95, 104.0, 298.0, 14.19, 298.0, 14.10]	[104.0, 104.0, 4.95, 104.0, 4.95, 298.0, 14.10, 298.0, 14.10]	[104.0, 4.95, 104.0, 104.0, 4.95, 298.0, 14.19, 298.0, 14.19]
SoC	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 0.0, 14.19, 298.0, 1.0, 15.14]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, 0.0, 14.19, 298.0, 0.0, 14.19]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, -0.0, 14.19, 298.0, -0.0, 14.19]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 298.0, -0.0, 14.19, 298.0, -0.0, 14.19]	[104.0, 0.0, 4.95, 104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 1.0, 15.14, 298.0, 1.0, 15.14]	[104.0, -0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, -0.0, 14.19, 298.0, -0.0, 14.19]	[104.0, -0.0, 4.95, 104.0, 0.0, 4.95, 104.0, 104.0, 104.0, 298.0, 2.0, 16.10, 298.0, 1.0, 15.14]	[104.0, 0.0, 4.95, 104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 298.0, -0.0, 14.19, 298.0, 2.0, 16.10]	[104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 104.0, 0.0, 4.95, 298.0, 2.0, 16.10, 298.0, 2.0, 16.10]	[104.0, -0.0, 4.95, 104.0, 104.0, 104.0, 104.0, -0.0, 4.95, 298.0, 0.0, 14.19, 298.0, -0.0, 14.19]
Km EV	803.0000	804.0000	804.0000	804.0000	802.0000	804.0000	801.0000	802.0000	800.0000	804.0000
Km TV	12.0000	0.0000	8.0000	16.0000	4.0000	0.0000	8.0000	12.0000	4.0000	0.0000
Total Solve Duration (s)	18.6506	19.6074	20.5631	22.7144	18.4425	19.4207	18.7223	18.6412	22.3217	19.0222

A.4 Torino Information

Table A.22: Distance between Lines and Depots (Meters)

Line	2	18	58	70	73	78	Tortona dis.	Gerbido
2	0	1529	11537	12845	3823	4630	2062	27591
18	1723	0	12815	14123	5101	4028	3014	27189
58	11924	12876	0	5420	8106	11523	3406	10588
70	12917	13869	5378	0	9098	12516	10900	19930
73	3981	4933	7995	9303	0	3580	1877	11761
78	5573	4425	11956	13264	4242	0	6344	34250
2	10129	10634	3913	2720	6989	8773	2062	27591
18	11382	32016	5097	3904	7941	7625	3014	27189
58	11924	12876	7037	8633	5207	14640	3406	10588
70	12917	13869	11016	10434	6239	15948	10900	19930
73	3981	4933	2622	2622	3231	6926	1877	11761
78	5573	4425	5611	3578	6588	4005	6344	34250
2	10129	11382	1645	3927	6612	10029	9044	7173
18	10634	32016	1491	6560	9246	12663	9836	4667
58	3913	5097	7037	11016	2622	5611	10537	6341
70	2720	3904	8633	10434	2622	3578	1470	21645
73	6989	7941	5207	6239	3231	6588	5603	11157
78	8773	7625	14640	15948	6926	4005	3502	33006

Table A.23: Line Characteristics and Timetables

Line	Frequency	Start time	End time	Duration	Kmts
2	75	[272, 290, 30...]	[332, 350, 36...]	60	15
18	92	[295, 318, 34...]	[349, 372, 39...]	54	13,5
58	95	[290, 302, 31...]	[319, 331, 34...]	29	7,25
70	18	[360, 400, 42...]	[410, 450, 47...]	50	12,5
73	11	[361, 410, 47...]	[383, 432, 49...]	22	5,5
78	24	[375, 410, 44...]	[388, 423, 45...]	13	3,25
2	74	[276, 294, 31...]	[336, 354, 37...]	60	15
18	92	[281, 304, 32...]	[335, 358, 38...]	54	13,5
58	95	[300, 312, 32...]	[329, 341, 35...]	29	7,25
70	18	[350, 370, 42...]	[400, 420, 47...]	50	12,5
73	10	[435, 500, 57...]	[445, 510, 58...]	22	5,5
78	24	[388, 423, 45...]	[401, 436, 47]	13	3,25

Model	Battery [kWh]	Consumption [Wh/100km]	Time of Charging 6.6 kWh[h]	Time of charging 80 kWh [h]	# Vehicles
Cacciamali Elfo	67	95	10.15	-	17
BYD K7	165	95	-	2.07	8
BYD K9(1)	324	104	49	4.05	50
BYD K9(2)	348	91	52,7	4.35	20

Table A.24: Electric Vehicles of GTT [31] before 2025

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