POLITECNICO DI TORINO

Master's Degree in Automotive Engineering

Master's Degree Thesis

Vehicle Simulation-based Planning of Recharging for Battery Electric Bus Fleets

Supervisors

Prof. Angelo BONFITTO

PhD Candidate Alberto PONSO

Candidate

Zhichao LIU

JUNE 2024

Summary

This study focuses on vehicle simulation-based charging planning for battery electric bus (BEB) fleets. As urban transportation shifts towards sustainable energy solutions, the adoption of BEBs is increasing. The driving range of BEBs can not guarantee that they can complete the specified tasks without charging for a whole day. Effective charging strategies are crucial to maximize vehicle utilization and minimize energy costs. This Master's Thesis introduces a four-step charging optimization model that integrates traffic conditions, driving cycles, SOC of battery, time-of-use tariffs and passenger numbers considerations. MATLAB-SUMO co-simulation was used to create unique driving cycles for each bus line at predefined times, capturing dynamic driver behavior, accounting for traffic flows and traffic lights. Using a backward energy consumption model, cost tables were developed that incorporate electric motor efficiency and braking energy recovery, reflecting trip length, trip duration variability, and energy consumption. An optimization algorithm was designed to minimize the number of BEBs and the overall electricity cost, considering time-of-use (TOU) tariffs, effectively optimizing the charging plan. The influence of passenger numbers on energy consumption was validated, with the maximum SOC difference between validated and optimized values remaining below 3%, confirming the practicality of the optimized charging plan. This study provides a feasible and efficient charging management solution for sustainable urban public transportation.

Acknowledgements

As the thesis comes to completion, I would like to express my sincere gratitude to everyone who has supported and helped me throughout this process.

First and foremost, I would like to extend my deepest thanks to my supervisor, Professor Angelo BONFITTO for the opportunity he gave me to write this thesis and explore this field of research. His valuable guidance, encouragement, and support have been crucial in the completion of this thesis.

I am also deeply grateful to Alberto PONSO for his unwavering support, timely assistance, and insightful suggestions over these months. His contributions have played a significant role in shaping my research, and the valuable opinions and feedback he provided have made my thesis more comprehensive and in-depth.

My heartfelt thanks go to my wife, whose support gave me the courage to study abroad. Her steady belief in me has been a source of immense strength. I would also like to thank my daughter, whose presence provided me with endless spiritual support and motivation. Special thanks to my parents and parents-in-law, who helped take care of our daughter and provided countless support, enabling me to focus on my studies.

In addition, I would like to thank my friends for their understanding and encouragement throughout my research. Their care and support have been an important source of motivation for me to persevere.

Finally, I would like to express my gratitude to all those who have helped and supported me during the research process. Your assistance has enabled me to successfully complete this work, and for that, I am sincerely thankful once again!

Table of Contents

List of Tables

List of Figures

Acronyms

BEB
: Battery Electric Bus

BEBs
: Battery Electric Buses

ICEBs
: Internal Combustion Engine Buses

EM
: Electric Machine

SOC
: State of Charge

TOU
: Time of Use

OSM
: OpenStreetMap

Chapter 1

Introduction

Air pollution caused by vehicles propelled by combustion engines is a pressing environmental concern with significant implications for public health and the environment [1]. As shown in Figure 1.1, the combustion of fossil fuels in vehicle engines releases a variety of pollutants, including sulfur dioxide (SO_2), nitrogen oxides (NO_X), particulate matter (PM), carbon monoxide (CO), and volatile organic compounds ($VOCs$), into the atmosphere [2]. These pollutants can have detrimental effects on air quality, leading to respiratory illnesses, cardiovascular diseases, and premature mortality among exposed populations [3][4].

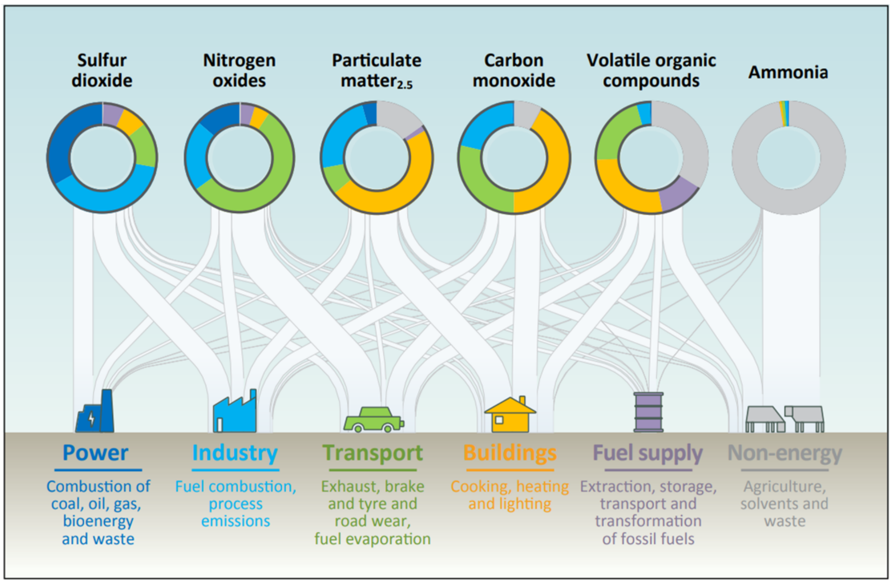


Figure 1.1: Selected primary air pollutants and their sources, 2015 [2]

Emission mitigation has emerged as a critical focus of the 21st century, with the adverse effects of continuously rising emissions becoming increasingly apparent on both global and local levels [5]. Reducing the usage of fossil fuels is widely recognized as a consensus measure to address this issue [6].

Public bus systems are a vital part of the multi-modal transportation network, offering passengers an affordable and environmentally friendly way to travel. As depicted in the Figure 1.2, between 2022 and 2050, passenger travel by bus in cities around the world is expected to nearly double [7].

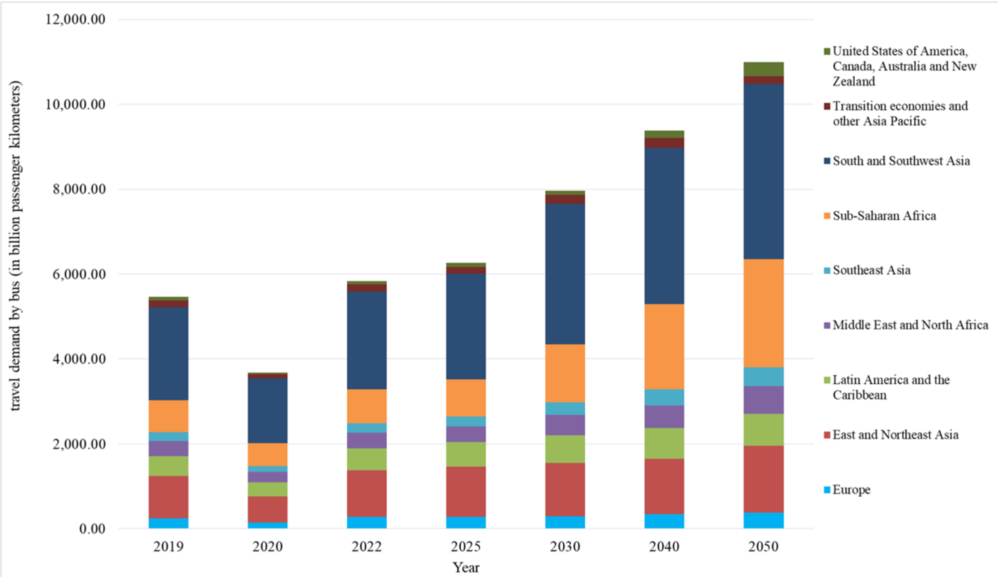


Figure 1.2: Global urban passenger travel demand for bus travel from 2019 to 2022 with a forecast through 2050, by region

Public bus systems are instrumental in alleviating traffic congestion and cutting down on exhaust emissions, thereby contributing significantly to urban sustainability and the reduction of the overall carbon footprint [8]. In 2022, diesel-powered buses remained the most popular in the EU, accounting for 67.3% of all new bus sales [9]. Traditional bus fleets, which predominantly rely on diesel engines, face challenges related to low energy efficiency, emissions, and dependency on oil. These issues not only impact the environment negatively but also lead to higher operational costs and dependency on fossil fuels [10].

In recent times, Battery Electric Buses (BEBs) have emerged as a promising alternative for traditional bus fleets, gaining increasing attention [11][12]. BEBs offer many advantages over their diesel counterparts. They boast superior energy efficiency, emitting zero tailpipe emissions, enhancing reliability, and offering maintenance benefits [13]. Moreover, BEBs have the flexibility to utilize renewable energy sources like wind, solar, and hydroelectric power, further solidifying their appeal as an environmentally sustainable option for public transportation [11][14].

Compared to other types of vehicles, public buses primarily operate in urban environments where their speed profiles are characterized by continuous accelerations and brakings [15]. This unique operational pattern is due to frequent stops for picking up and dropping off passengers at various points throughout the city. The need to accelerate and brake very frequently makes the regenerative braking capability of BEBs crucial. In BEBs, the energy during braking is captured and converted back into usable electrical energy, thereby significantly improving overall energy efficiency. This is in contrast to internal combustion engine buses (ICEBs), where the energy during braking is simply wasted as heat, resulting in higher fuel consumption and lower energy efficiency [13].

By employing the regenerative braking technology, BEBs can not only extend their range but also reduce the wear and tear on braking systems, leading to lower maintenance costs and longer service life [10][16]. This ability to recover and reuse energy highlights the importance of BEBs in creating a more sustainable and efficient urban transportation network. Furthermore, the reduction in tailpipe emissions contributes to improved air quality in urban areas, providing a healthier environment for residents [11][14].

Despite the considerable environmental advantages and energy efficiency of BEBs, their market penetration remains relatively constrained across most regions. In 2022, sales of new electrically-chargeable buses in the EU increased to reach 3,505 units, only accounting for 12.7% of the total EU bus market [9]. The primary drivers behind this phenomenon are the elevated purchase costs of BEBs and their limited driving range compared to alternative bus technologies.

The substantial cost of BEBs is primarily attributed to the expensive lithium-ion battery technology, which accounts for nearly one-third of the total bus cost. Despite notable reductions in lithium-ion battery costs over the past decade, it is expected to remain relatively expensive for the foreseeable future [17].

Diesel buses boast a maximum driving range exceeding 300 km in urban conditions [18]. In contrast, most electric buses currently available on the market offer a maximum driving range ranging from 70 km to 200 km. This range is 25% to 65% less than that of diesel buses, posing challenges for continuous operation without the need for recharging [11].

This driving range constraint of BEBs proves to be especially challenging. The relatively long time required by battery recharging is a significant factor. In comparison, refuelling diesel vehicles, the currently dominant technology in local transportation, is much quicker [19]. For example, a Build Your Dreams (BYD) BEB equipped with a 547 kWh battery pack would require over 20 hours to reach full charge when utilizing a charging power of 20 kW.

The emerging technology of fast charging holds promising potential to alleviate the aforementioned drawbacks associated with BEBs about recharging time. Fast-charging stations with a charging power up to 350 kW have been available in the market [20]. Fast-charging technology enables BEBs to take advantage of the dwell time between trips to rapidly recharge its battery. This capability allows the BEBs to sustain continuous on-route operations even with a relatively modest battery capacity. But it may significantly increase electricity costs and thus lead to high operating costs.

Although fast-charging technology indeed enables continuous BEBs operations, it also presents a double-edged sword. On one hand, fast charging offers the advantage of shorter recharging times, which is beneficial for meeting urgent charging needs. On the other hand, it also poses risks such as deteriorating battery safety, accelerating battery degradation, and necessitating advanced electric charging equipment [21][22].

Given these obstacles, a critical daily operational concern for BEBs is devising cost-effective schedules and coordinating charging activities. This entails considering various constraints, including physical, financial, institutional, and managerial factors. Inadequate charging scheduling and management can exacerbate operational challenges, heighten range anxiety, raise charging and operating costs, diminish the economic appeal of electric buses, and impose substantial strain on the power grid [23][24]. There has been extensive research conducted on recharging scheduling for BEBs [25][26][27].

The actual driving range of BEBs from a full charge can be influenced by a variety of factors, including the state of charge (SOC) of battery, drivers' driving behaviors, traffic conditions, efficiency of Electric Motor (EM) and number of passengers on the BEB. However, in the studies we mentioned above, the energy consumption rate of bus batteries during electric bus operation is assumed as a constant, and not considered the influence of SOC of battery, drivers' driving behaviors, traffic conditions, efficiency of Electric Motor (EM) and number of passengers on the BEB.

The objective of this Master's Thesis is to address and solve the identified weaknesses of the existing framework. We have developed a four step working flow to optimize the charging activity of BEB fleets, whose objective is to minimize both the number of BEBs and the cost for charging them.

First, we build simulation-based driving cycles taking into account the influence of traffic condition, drivers' driving behaviors and time of day which is close to actual bus operating conditions. Second, we construct cost tables that provide a more precise energy consumption rate. These tables are based on a backward vehicle simulator, which takes into account the efficiency of EM, SOC of battery, brake energy recovery and number of passengers. Furthermore, we proposes an optimization algorithm for planning of recharging for BEBs, in order to minimize both the number of BEBs and the electricity costs of daily operation of BEB Fleets. Finally, we validate the feasibility of our optimal charging plan for BEB fleets based on variable passengers on them.

The findings and insights gained from this research contribute to the advancement of the field and offer potential solutions to the existing limitations, thereby offering promising avenues for further research and development.

Chapter 2

State of Art

As stated in Chapter 1, this Master's Thesis has developed a four-step methodology to plan the charging activity of BEB fleets with the aim to minimize both the number of BEBs and the total cost to charge them.

To better develop our methodology, we have explored deeply into the BEB charging scheduling problem. Additionally, we have thoroughly examined the energy consumption patterns of BEBs and the vehicle models used for BEBs, ensuring a comprehensive understanding of all relevant factors.

2.1 Charging Scheduling for BEB Fleets

Many authors have addressed the charging scheduling problem, focusing on minimizing charging costs and managing the power load at charging stations. Under dynamic electricity demands and fluctuating electricity prices, the operating electricity cost is highly dependent on the charging schedule. Additionally, electric bus charging stations consume significant amounts of power, making it essential to arrange charging schedules properly to minimize energy costs.

An optimization charging scheduling framework for BEBs in an urban public transit network was proposed [25]. This framework features a mixed-integer programming optimization model that considers both the configuration of the transit bus network and the technical characteristics of fast charging systems. The proposed optimization framework aims to minimize the total costs of operating an electric bus recharging system and determines both planning decisions, such as the location and capacity of charging stations, and operational decisions, such as recharging schedules. However, it's important to note that they utilize a constant value for unit travel cost and do not consider traffic conditions in their model.

Another comprehensive modeling framework was presented which was designed to optimize charging scheduling and management for a fast-charging BEBs system [26]. They have tackled the optimal charging scheduling problem for a fast-charging battery electric bus system, taking into account electricity demand charges and time of use (TOU) rate structure. A limitation of their study is that it assumes a deterministic nature, where both the timetable and the energy consumption of BEBs are predetermined parameters. Additionally, their study considers an electric bus system with predefined fleet size, battery capacity, and bus line schedules, which may not fully capture the dynamic nature of real-world transit operations.

Recently, a mixed-integer programming model with a linear structure for the proposed charging scheduling problem was developed [27]. Their model incorporates various factors, including individual electricity charging and consumption rate restrictions, charging window constraints, battery electricity level limits, TOU charging tariffs, and site-specific electricity load capacities, ensuring a comprehensive approach to optimizing charging scheduling. The mixed linear integer programming model proposed by them is both concise and versatile, making it suitable as a foundational component in more intricate optimization problems related to electric bus system development and management. But, it's worth highlighting that their study utilizes a constant value for unit travel cost and does not account for traffic conditions too.

In the studies we just discussed, none have taken into account the variability of energy consumption, which is influenced by several dynamic factors. These factors include traffic conditions, which can significantly impact energy usage, as well as other elements such as SOC of BEBs and driving behavior. By neglecting these variables, the models may not accurately represent real-world scenarios, potentially leading to suboptimal planning and increased operational costs.

2.2 Energy Consumption of BEBs

In literature, energy consumption of BEBs is determined through different possible methods. We will discuss three approaches in the flowing section.

2.2.1 Energy Consumption per Unit of Distance or Time

This approach, while straightforward, involves using a single average energy demand value for each type of bus across all routes. It's commonly employed in studies focusing on scheduling problems for BEBs. For instance, in a case study in Penghu, Taiwan, energy requirements for local bus lines are calculated based on route distance and fixed specific energy demand values for different-sized e-buses [28]. Similarly, a single average energy demand values was used, assuming them to be proportional to total driving distance with no variations throughout the day [25] [29]. Another example, a study on charging infrastructure requirements in Stockholm, Sweden, the energy demand for the entire bus network was calculated based on real trip schedules but assumed it to be proportional to trip distance [30].

While simple to implement, this approach provides only a rough estimate of energy demand and overlooks variations in traffic conditions and route characteristics such as inclines and declines. Moreover, it fails to account for auxiliary power consumption, which is drawn constantly, primarily for air conditioning or heating. Consequently, energy demand due to auxiliary power depends more on trip duration than trip distance. During peak hours, bus journeys may take considerably longer, leading to substantially higher energy demand.

2.2.2 Energy Consumption by Using a Standard Driving Cycle

In this approach, standard driving cycles sourced from literature are utilized. These cycles are derived from traffic measurements conducted in various cities, with examples including the Braunschweig, New York City, Orange County, or Paris bus cycles. Each driving cycle exhibits unique characteristics, and an overview of these can be found in [31].

Previous studies typically select a driving cycle resembling the conditions of their study area. For instance, in a literature, several standard driving cycles were examined and the one with a similar number of bus stops to their study city was chosen [32]. However, potential differences in traffic conditions, particularly during peak hours, are not considered. A step forward, in another literature, six different driving cycles were used to conduct simulations, then the one that best matched each bus line's characteristics was selected [33]. A model of bus energy consumption derived from a standard driving cycle was employed on a small network of seven bus lines in another study [34].

Standard driving cycles encompass variations such as highway driving or congested traffic. Yet, applying a standard driving cycle from one city to another inevitably results in discrepancies, as traffic conditions vary between cities and even within different bus routes within a city. Several driving cycles for heavy-duty vehicles, including buses, were analyzed, concluding that these cycles can differ significantly from real-life conditions [31]. This is particularly true for bus services, given their low average speed, frequent stops, and high deceleration/acceleration before/after reaching a stop. A new driving cycle based on real operation data was constructed, emphasizing the importance of reflecting actual driving characteristics for credible test results [35]. However, creating an adapted driving cycle is complex and requires numerous measurements, a process that needs to be repeated for each bus route.

2.2.3 Energy Consumption from Detailed Measurements of Driving Profiles

To obtain more accurate values for bus energy demand, measurement equipment can be installed onboard buses to record energy consumption with high temporal resolution. Simulation models can then be derived from these results. For instance, a longitudinal dynamics model was developed in a case study for a loop line in Aachen, Germany [36]. They derived route characteristics from waypoints defined via an internet mapping service, such as stop duration and speed limit. The vehicle model was validated with traction power measurement data from the operation of serial hybrid buses in another city and applied to various bus lines in Germany. Later, this model was used as a preprocessing step for energy demand calculations in Muenster, Germany, and Aachen [37]. However, the authors once again did not elaborate on how the actual speed profile used in the longitudinal dynamics model was generated. The velocity profile of a bus line in Berlin was recorded using a GPS sensor and created an energy demand model [38]. This model was validated using data from installed equipment measuring speed, auxiliary power, and battery state of charge on electric buses. The representativeness of laboratory testing and installed onboard data collectors in BEBs was examined for a demonstration project in Macao [39]. A large dataset of measurements from diesel buses was used in Knoxville, USA, to evaluate energy demand and charging needs for city transit electric buses [40]. They suggested significant cost savings on battery investment could be achieved with flexible battery configurations and charging strategies based on individual driving characteristics of bus routes.

However, approaches requiring field-test measurements have inherent scalability limitations. While manageable for small bus networks, measuring the driving profile of each bus route becomes impractical for larger networks. Additionally, detailed measurements are typically carried out for only a few buses, leading to challenges in considering all bus lines and variations in traffic conditions. Multiple measurements would be needed for each bus line to account for traffic conditions fully.

2.3 Vehicle Energy Consumption Models

Vehicle energy consumption models can be divided into two categories: Forward approach also called "dynamic approach" or cause-effect method, and Backward approach also called "quasi-static approach" or effect-cause method [41][42].

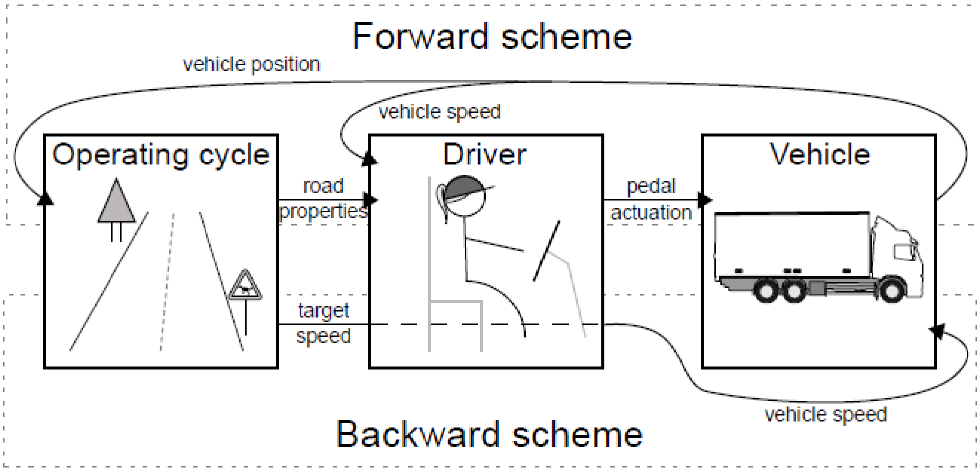


Figure 2.1: The imagined simulation model topology, with the forward scheme showed top and the backward scheme showed bottom [41]

2.3.1 Forward model

In the forward scheme, a target speed is provided by a driving cycle and processed through a driver model. The driver model controls the vehicle's longitudinal interfaces—the accelerator and brake pedals—based on the difference between the target speed and the actual vehicle speed. The energy carrier is injected into the prime mover, and the resulting torque is transmitted forward through the powertrain to the wheels, generating the traction needed for propulsion. Newton's second law is applied to determine the vehicle's acceleration, which is then integrated to obtain speed and position. This position is fed back into the driving cycle to determine the new target speed, thus closing the computational loop. The flow of effort in the powertrain is opposite to that in the backward method, hence the term "forward" method. Given that this approach more closely mirrors real-world dynamics, a more accurate term might be "causal" simulation. Figure 2.1 shows this method in the upper part [41].

In a study, the authors developed an equation-based forward model capable of predicting the real-world energy consumption of electric city buses with remarkable accuracy [43]. Using this model, they investigated the influence of several significant unmeasured factors, including driving style, elevation profile, number of stops, route type, and traffic conditions, on energy consumption. They found that the synthesized best- and worst-case scenarios for these factors resulted in energy consumption variations ranging from 0.19 kWh/km to 1.34 kWh/km, representing a twofold variation from the nominal value. These off-nominal factors must be considered when sizing components and planning range limits for BEBs.

In another study, the authors developed a forward model for a 52 V battery electric vehicle [44]. Based on this model, they examined the impact of rolling resistance on the energy consumption of vehicles, particularly compact electric vehicles in urban scenarios. They found that the rolling resistance contribution due to longitudinal slip increases the vehicle's electric efficiency by 0.7 to 0.8 $kWh/100km$ compared to a constant coefficient model.

Additionally, the authors proposed a method for selecting the optimal equivalence factors for charging and discharging by applying a genetic algorithm to a P0 mild hybrid electric vehicle, which they modeled as a forward model in their study [45]. Their method provides a systematic and deterministic approach to guarantee an optimal solution, unlike the trial-and-error method. Compared to a technique known as the shooting method, their approach always ensures an optimal solution, even under heavy accessory load conditions, where the shooting method fails to guarantee a charge-sustaining condition.

There is one thing that needs to be pointed out, even though the forward model is more accurate than the backward approach, the forward approach requires more computational effort to solve it's differential equations [46].

2.3.2 Backward model

In the backward scheme, a target speed is provided by a driving cycle. The necessary propulsion force is computed from Newton's second law and it, together with the vehicle speed, is propagated from the wheels, through the powertrain, to the prime mover where the necessary input power for the propulsion effort is computed. The approach is called backward because the data flows backwards through the powertrain, but another descriptive name would be 'inverse dynamic' simulation. The arrows in the lower part of Figure 2.1 depict the method [41].

A backward vehicle model of a fuel cell hybrid electric vehicle was developed and validated in a study [47]. This model is noted for its speed and the reliability and consistency of its results, as it simulates all vehicle components over several driving cycles. Using this backward vehicle model, the authors investigated the optimal power split between the fuel cell and the battery, employing an ECMS control method for fuel cell vehicles. They found that the model performs well for low-load driving cycles such as WLTC, NEDC, JC08, and US06, with an error of less than or approximately equal to 10%.

Another backward model named "VT-CPEM" was developed to compute the instantaneous energy consumption of electric vehicles based on the instantaneous power exerted [48]. This model uses vehicle speed and acceleration levels as input variables. It complements existing backward vehicle simulators by modeling the efficiency of instantaneous regenerative braking energy as a function of deceleration levels. Additionally, due to its simple formulation, the model can be easily integrated into microscopic traffic simulation software as well as vehicle and smartphone eco-driving and eco-routing applications. The proposed model accurately estimates energy consumption, with an average error of 5.9% relative to empirical data.

Chapter 3

Methodology

The planning of recharging for BEB fleets, which is the primary focus of this Master's thesis. We attempt to determine the optimal number of BEBs required and the charging events for each individual BEB within the fleets, with the objective of minimizing the total cost of purchasing BEBs and the overall charging cost of the BEB fleets during a standard operational day. However, there are still constraints that must be taken into account during this process. For instance, the availability of charging infrastructure, the limitations of SOC of BEBs, and the limitations imposed by the existing energy grid. The detailed working flow is shown in Figure 3.1.

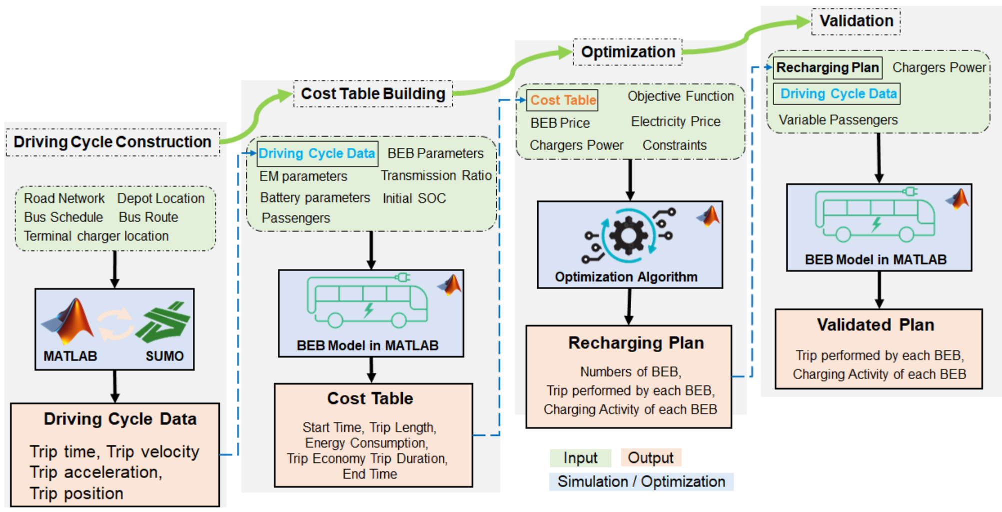


Figure 3.1: Architecture of Working Flow

The working flow presented in this Master's Thesis can be subdivided into four separate steps, which are **Driving Cycle Construction**, **Cost Table Building**,

Optimization, and **Validation**. Each of these can be imagined as a block receiving input from the previous step and generating an output for the following one.

Each block is subdivided into three subsections: *Input*, *Simulation or Optimization*, and *Output*. Once a section is completed, the transition to the next can be made seamlessly. Detailed exploration of each block and its corresponding subsections will be presented in the following sections.

3.1 Vehicle Energy Consumption Model

Vehicle energy consumption model assumes a crucial position in the overall process of constructing the cost table via energy consumption estimation via backward model simulation.

3.1.1 Parameters of BEB

In this Master's thesis, we will model a BYD BEB, as illustrated in Figure 3.2, which services in Torino. BYD's 40-foot eBus remains as the best-selling electric bus model with over 700 vehicles already in service in Europe. The overall dimensions are 12.2×2.55×3.3 meters, and the maximum passenger capacity is 90. The BEB is driven by two wheel hub motors.

Figure 3.2: The BEB Utilized in Thesis (Serviced in Turin)

The detailed parameters of the BEB are detailed in Table 3.1.

3.1.2 Backward Vehicle Energy Consumption Model

As the battery acts as the primary and exclusive energy source in a BEB, it plays a crucial role in providing the necessary power not only for the propulsion of the vehicle but also for the operation of various accessories that are essential for its overall functioning. Consequently, we can take advantage of a backward vehicle

Parameter	Symbol	Value
Vehicle Curb Mass	m_{curb}	12880 kg
Frontal Area	A_f	8.5 m^2
Aero-Drag Coeff.	C_d	0.79 [49]
Rolling Resistance Coeff.	C_r	0.01
Passengers Capacity	c_{pas}	90
Passenger Mass	m_{pa}	68 kg
Tyre Data	-	275/70 R22.5
Transmission Ratio	i	22
Max. EM Power	P_{em-max}	150*2 kW
Max. EM Torque	T_{em-max}	550*2 Nm
Max. EM Speed	n_{em-max}	10000 rpm
Nominal Capacity of Battery	C_{bat}	600 Ah
Nominal Voltage of Battery	V_{bat}	537.6 V
Nominal Energy of Battery	E_{bat}	322.56 kWh

Table 3.1: BEB Main Parameters

energy consumption model, which is graphically represented in Figure 3.3, in order to accurately calculate and determine the total energy consumption of the vehicle, thereby enabling us to gain a deeper understanding of its energy requirements.

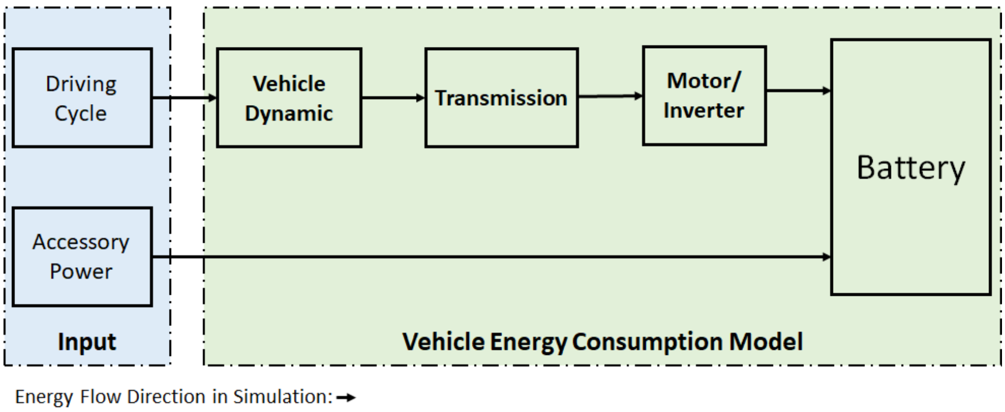


Figure 3.3: Backward Vehicle Energy Consumption Model

Mathematical Model of BEB

In the following section, the mathematical model employed to approximate the BEB under study is presented.

Vehicle Dynamic

In this section, we will discuss two main topics. Firstly, we'll dive into vehicle longitudinal dynamic, focusing on calculating the traction power at the wheels. Secondly, we'll explore wheels dynamic, aimed at calculating the angular speed of the wheels and the traction torque generated.

Vehicle Longitudinal Dynamic

As a starting point, the vehicle longitudinal dynamics serves as the theoretical framework for estimating the tractive effort F_t(N) required to overcome resistance forces and accelerate the vehicle. Specifically, the tractive effort refers to the propulsive force transmitted to the ground through the wheels, driving the vehicle forward, as seen in Equation 3.1:

$$F_t = F_{aero} + F_{roll} + F_{hc} + F_{acc} \tag{3.1}$$

The overall required tractive force (F_t) is considered positive when the battery has to supply power to the motor, and negative when the motor operates as a generator.

The equivalent aerodynamic drag force, F_{aero}, on a vehicle can be represented as:

$$F_{aero} = \frac{1}{2}\rho C_d A_f (V_x + V_{wind})^2 \tag{3.2}$$

where ρ (kg/m^3) is the mass density of air, C_d is the aerodynamic drag coefficient, A_f (m^2) is the frontal area of the vehicle, which is the projected area of the vehicle in the direction of travel, V_x (m/s) is the longitudinal vehicle velocity, V_{wind} (m/s) is the wind velocity (positive for a headwind and negative for a tailwind).

Atmospheric conditions affect air density ρ and hence can significantly affect aerodynamic drag. The commonly used standard set of conditions to which all aerodynamic test data are referred to are a temperature of $15°C$ and a barometric pressure of 101.32 kPa [50]. The corresponding mass density of air ρ is taken as 1.225 kg/m^3.

The rolling resistance force (F_{roll}) arises primarily from the interaction between the vehicle's tires and the road surface, represented as:

$$F_{roll} = C_r mg * cos(\alpha) \tag{3.3}$$

where C_r is rolling Resistance coefficient, m is the total mass of the vehicle, comprising both the curb mass of the vehicle and the mass of passengers onboard. g (m/s^2) is the acceleration due to gravity, the corresponding value is taken as 9.8 m/s^2. α is the angle of inclination of the road on which the vehicle is traveling. The angle α is defined to be positive when the vehicle is uphill and is defined to be negative when the vehicle is downhill.

The hill climbing force (F_{hc}) denotes the gravitational force component that acts on a vehicle when ascending a inclination angle α, defined as:

$$F_{hc} = mg * sin(\alpha) \tag{3.4}$$

In accordance with Newton's second law of motion, the force F_{acc} required to achieve linear acceleration in a vehicle is expressed by:

$$F_{acc} = m * a \tag{3.5}$$

where a (m/s^2)is the linear acceleration of the vehicle.

Wheels Dynamic

The traction force exerted by the vehicle is directly produced by the torque applied to the wheels, which can be calculated by:

$$T_{wheel} = F_t * r_{wheel} \tag{3.6}$$

where r_{wheel} (m) is the effective radius of the wheels. The torque applied to the wheels (T_{wheel} (Nm)) is considered negative when the vehicle is braking.

The angular speed of the wheels (ω_{wheel} (rad/s)) can be calculated by:

$$\omega_{wheel} = \frac{V_x}{r_{wheel}} \tag{3.7}$$

Transmission System

In our vehicle model, the wheels are not directly connected to the motor shaft. Instead, the transmission system, a single ratio gear system, is used to convert the torque generated by the motor into the torque required at the wheels. The output shaft of the transmission system is connected to the wheels, so the output angular speed of transmission system equals to the angular speed of wheels. The input angular speed of transmission system, $\omega_{t,in}$ (rad/s), can be determined using:

$$\omega_{t,in} = \omega_{wheel} * i \tag{3.8}$$

The output torque of transmission system equals to the torque of wheels. The input torque of transmission system is calculated by:

$$T_{t,in} = \frac{T_{wheel}}{i} * \eta_t^{-sign(T_{wheel})} \tag{3.9}$$

where η_t is the efficiency of the single ratio gear system, which is taken as 0.98 [49].

Electric Machine

The shaft of the EM is linked to the input shaft of the transmission system. Consequently, we can derive the angular speed and torque of the electric motor from:

$$\begin{cases} \omega_{EM} = \omega_{t,in} \\ T_{EM} = T_{t,in} \end{cases} \tag{3.10}$$

So, the mechanical power of EM can be calculated by:

$$P_{EM,M} = T_{EM} * \omega_{EM} \tag{3.11}$$

The mechanical power ($P_{EM,M}$) can be positive or negative. If $P_{EM,M} > 0$, the EM works as electric motor, converting electrical energy into mechanical energy which is provided to the wheels. If $P_{EM,M} < 0$, the EM works as generator, converting mechanical energy which is provided by the wheels into electrical energy. This process can be represented by:

$$P_{EM,E} = \begin{cases} \frac{P_{EM,M}}{\eta_{EM}} & \text{for } P_{EM,M} > 0 \\ P_{EM,M} * \eta_{EM} & \text{for } P_{EM,M} < 0 \end{cases} \tag{3.12}$$

where η_{EM} is the efficiency of EM.

To enhance the precision of modeling the motor's behavior, in the model proposed by this Master's Thesis, we implement a lookup table mechanism to access the efficiency data of EM, shown in Figure 3.4.

In this Master's thesis, it was assumed that the torque-speed relationship in generator mode mirrors that in motor mode, as shown in Figure 3.4, provided that the braking torque remains below or equal to the maximum generator torque. This assumption, already established in the literature, ensures consistency in modeling [51]. However, if the braking torque exceeds this limit, the surplus power is dissipated as heat due to mechanical braking.

Additionally, the regenerative braking system does not apply any braking force at low vehicle speeds, as the available torque is insufficient [51]. To simulate this

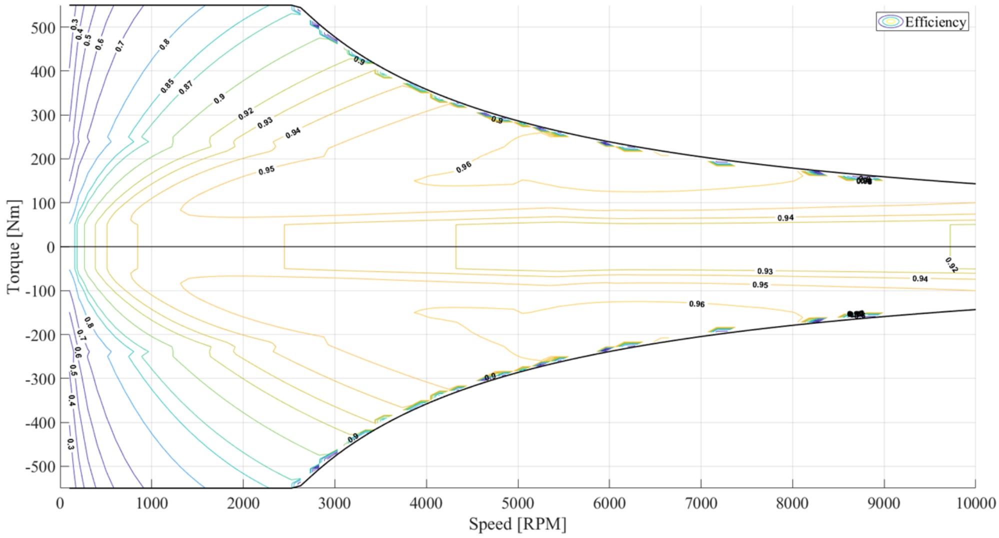


Figure 3.4: Efficiency Map of EM

operation, the vehicle model integrates a speed-dependent regeneration factor, denoted as f_{reg}. This factor indicates the proportion of available regenerative braking power that can practically be recovered based on the vehicle's speed (V_x). It's worth noting that there exists a threshold speed (v_1) that must be surpassed for the electrical machine to initiate energy regeneration [52]. Moreover, the EM achieves its maximum regeneration capability for speeds exceeding another threshold (v_2). For speeds between v_1 and v_2, it's assumed that the percentage of recoverable braking power increases linearly with the vehicle's speed until reaching the maximum regeneration capability. In this project, the two speed thresholds were set as $v_1 = 10\ km/h$ and $v_2 = 30\ km/h$, shown in Figure 3.5.

Considering the aforementioned details, Equation 3.12 can be re-formulated as follows:

$$P_{EM,E} = \begin{cases} \frac{P_{EM,M}}{\eta_{EM}} & \text{for } P_{EM,M} > 0 \\ P_{EM,M} * \eta_{EM} * f_{reg} & \text{for } P_{EM,M} < 0 \end{cases} \tag{3.13}$$

Battery

Since the work of this thesis is focused on BEB, the only energy source is the battery, unlike hybrid vehicles, no engine is present. Through inverter, the electric power ($P_{EM,E}$) required at EM level is converted into electrical power (P_{batt}) required at battery level.

$$P_{batt} = \begin{cases} \frac{P_{EM,E}}{\eta_{Inv}} + P_{aux} & \text{for } P_{EM,E} > 0 \\ P_{EM,E} * \eta_{Inv} + P_{aux} & \text{for } P_{EM,E} < 0 \end{cases} \tag{3.14}$$

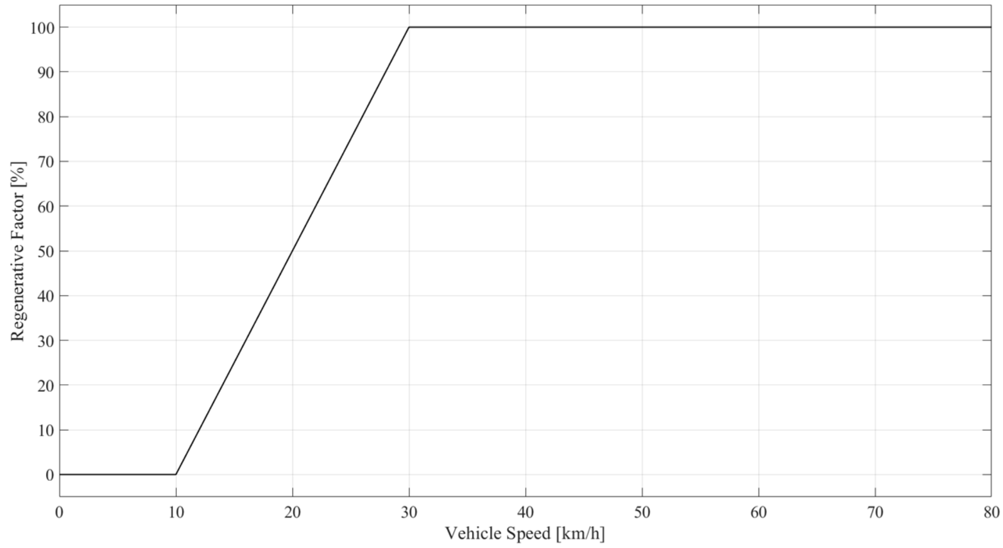


Figure 3.5: Speed-dependent regeneration factor

where $\eta_(inv)$ is the efficiency of the inverter, which is taken as 95%, and P_{aux} is the power consumed by auxiliary, which is taken as 10 kW.

The battery open-circuit voltage ($V_{OC}(V)$) and its internal resistance ($R_{eq}(\Omega)$) are depending on the instantaneous values of SOC and scaled with the number of cells in parallel and series.

$$V_{OC} = V_{OC}(SOC) \tag{3.15}$$

$$R_{eq} = R_{eq}(SOC) \tag{3.16}$$

The battery open-circuit voltage and its internal resistance used in this thesis are shown separately in Figures 3.6 (a) and (b).

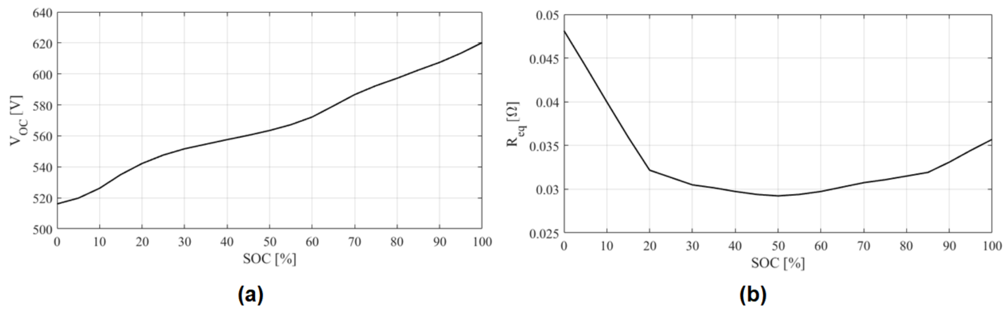


Figure 3.6: Battery Property: (a) Open-Circuit Voltage (b) Internal Resistance

The current drawn from the battery and the SOC are computed as follows [53]:

$$I_{batt} = \frac{V_{OC} - \sqrt{V_{OC}^2 - 4 * R_{eq} P_{batt}}}{2 * R_{eq}} \tag{3.17}$$

$$SOC(t+1) = SOC(t) - \frac{I_{batt}}{C_{batt}} \frac{t_{step}}{3600} \tag{3.18}$$

3.2 Related Software

It is clear from Figure 3.1, two distinct software applications were utilized: MATLAB and SUMO [54][55]. The majority of the work was conducted in the MATLAB environment. Only the first block involved SUMO, the remaining three blocks were all executed using MATLAB.

MATLAB is a programming and numeric computing platform used by millions of engineers and scientists to analyze data, develop algorithms, and create models [54]. MATLAB combines a desktop environment tuned for iterative analysis and design processes with a programming language that expresses matrix and array mathematics directly. It includes the Live Editor for creating scripts that combine code, output, and formatted text in an executable notebook.

SUMO, an open-source traffic simulation software designed for analyzing transportation systems and simulating traffic scenarios [55]. SUMO was employed specifically for simulating the BEB dynamics considering the traffic light and traffic flows in the first block.

In the first block, MATLAB served as the primary platform for executing the co-simulation, seamlessly integrating with SUMO through the utilization of TraCI4Matlab [56]. TraCI4Matlab is a specialized implementation of the TraCI protocol tailored to the MATLAB environment, facilitating smooth communication between the two software tools. This integration enables seamless interaction, with SUMO acting as the server fulfilling MATLAB's requests as the client. A literature proposed a route planning method for electric vehicles and the authors conducted the route testing via Matlab–SUMO co-simulation instead of real-life on-road tests. Their results show that the robustness offered by the energetic estimation has been improved compared with a standard planning method, which uses the same cost function to select the stations but only considers nominal electric vehicle range [53].

Co-simulation was chosen to construct the driving cycle because it offers a more accurate simulation of BEB dynamics during operation on a fixed bus route. Velocity and acceleration profiles were obtained from MATLAB-SUMO co-simulation, operating with a time step of 1 second. The decision to employ SUMO for driving cycle construction was driven by its powerful capabilities and fast computation speed. As a traffic simulator, SUMO is well-suited for simulating the impact of traffic conditions and vehicle flows, making it a suitable choice for this project.

3.3 Driving Cycle Construction

To construct driving cycles, we have to understand the operational pattern of BEBs throughout the day. Figure 3.7 illustrates the spatial operations of BEBs.

Initially, all BEBs commence their first trip from the depot, denoted as "*depot* → *terminal*". Subsequently, they carry out their daily tasks, represented by "*terminal* → *terminal*". If charging is required during their dwell time at terminal, BEBs proceed to the terminal charger station, depicted as "*terminal* → *terminal charger*". Once charging is completed, they return to the same terminal, indicated by "*terminal charger* → *terminal*". Finally, upon completing all tasks, BEBs return to the depot, represented by "*terminal* → *depot*". This schematic provides an overview of the operational sequence followed by BEBs throughout the day.

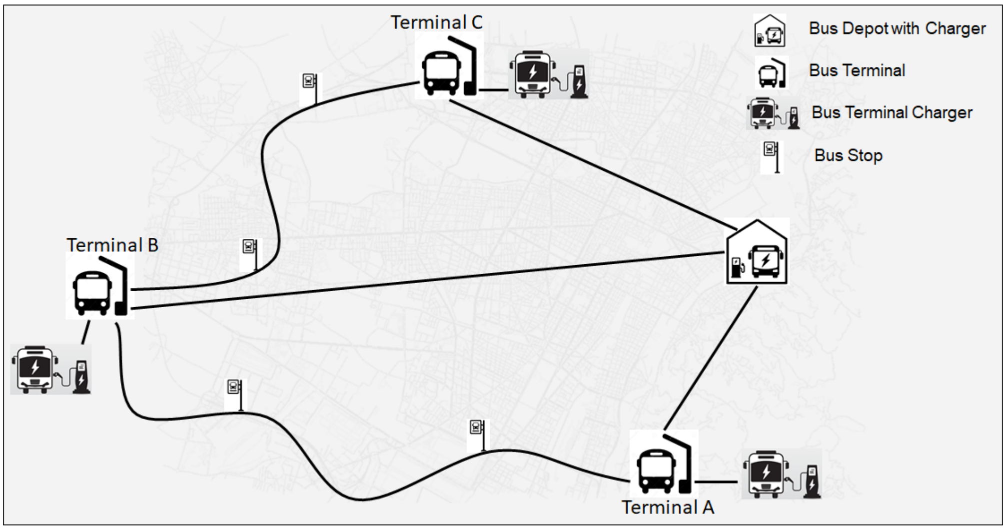
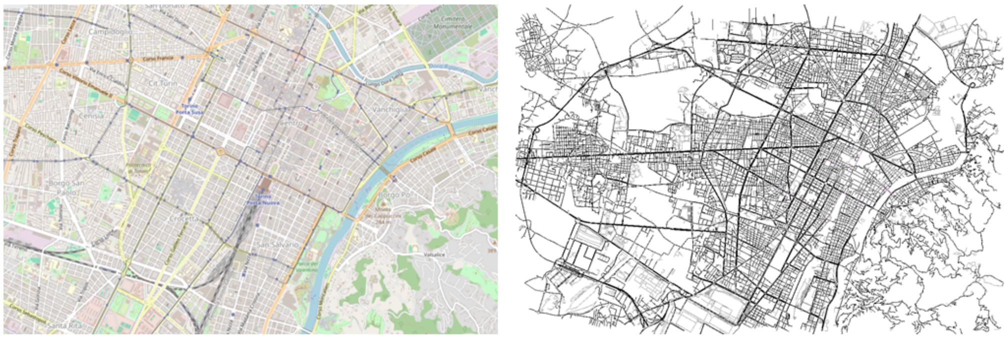


Figure 3.7: Illustrative example of a spatial operation of BEBs

BEB operations have been categorized into five distinct types. In general, the terminal charger stations are built inside the terminal stop or very close to it. Because of this, in this Master's thesis, we will not construct the driving cycle of "*terminal* → *terminal charger*" and "*terminal charger* → *terminal*". Notably, the operation "*terminal* → *terminal*" is unique in that it involves passengers being transported on the BEB, whereas the trips of "*depot* → *terminal*" and "*terminal* → *depot*" do not involve the presence of passengers on the BEB.

3.3.1 Road Network

The road network in this Master's thesis is the urban region of Torino. As shown in Figure 3.8, the network is represented in SUMO framework, and sourced from OpenStreetMap (OSM) website, an online cartographic service constantly updated and constructed by volunteer contributors, accessible under an open-content license [57].



(a) (b)

Figure 3.8: Road Network of Torino: (a) OpenStreetMap (b) SUMO Framework

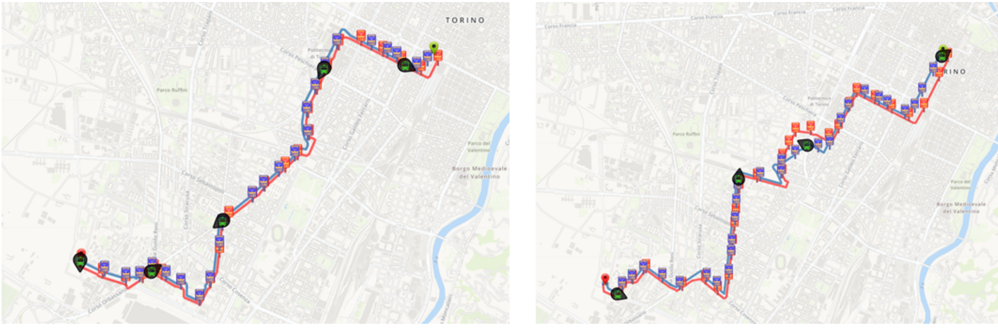
A SUMO network file describes the traffic-related part of a map, the roads and intersections the simulated vehicles run along or across. At a coarse scale, a SUMO network is a directed graph. Nodes, named "junctions" in SUMO-context, represent intersections, and "edges" roads or streets. Note that edges are unidirectional. Specifically, the SUMO network contains the following information [55]:

- Every street (edge) as a collection of lanes, including the position, shape and speed limit of every lane,
- Traffic light logics referenced by junctions,
- Junctions, including their right of way regulation,
- Connections between lanes at junctions (nodes).

3.3.2 Bus Route

In this Master's thesis, the attention was focused on bus lines 12 and 58. The bus routes and stops shown in Figure 3.9, were obtained from the website of GTT, Turin's public transportation company [58].

These two lines consist of three terminals: "VITTORIO EMANUELE II CAP", "ALLASON CAP" and "BERTOLA CAP", with "ALLASON CAP" serving as a



(a) (b)

Figure 3.9: Bus Lines of Torino: (a) Bus Line 12 (b) Bus Line 58

common terminal. For simplicity, we will denote "VITTORIO EMANUELE II CAP" as T_A, "ALLASON CAP" as T_B, and "BERTOLA CAP" as T_C. Each bus line can be segmented into two sections according to the trip direction. The specific trip lengths and stops are provided in Table 3.2.

Bus Line	Trip Direction	Trip Length (km)	Trip Stops
Bus Line 12	$T_A \rightarrow T_B$	8.2	24
	$T_B \rightarrow T_A$	8.2	25
Bus Line 58	$T_B \rightarrow T_C$	9.6	29
	$T_C \rightarrow T_B$	9.4	28

Table 3.2: Trip Lengths and Stops of Bus Lines

In the following section, For bus line 12, we refer to "$T_A \rightarrow T_B$" as "Line 12 Southward" and "$T_B \rightarrow T_A$" as "Line 12 Northward". For bus line 58, we refer to "$T_B \rightarrow T_C$" as "Line 58 Northward" and "$T_C \rightarrow T_B$" as "Line 58 Southward".

As previously discussed, it is essential to note that the edges in the SUMO framework have a direct correlation with the actual roads that exist in reality. By carefully referencing the real bus route, we are able to gather the unique edge IDs in SUMO, which is a crucial step in enabling us to construct the bus route in MATLAB.

In the MATLAB environment, routes are typically expressed as ordered arrays of cells, where each individual cell is used to indicate the corresponding edge ID, as illustrated in Figure 3.10. This figure provides a visual representation of how the bus route is constructed using the edge IDs, and it serves as a valuable resource for understanding the underlying concepts.

Although a limitation exists in the current road framework, specifically with

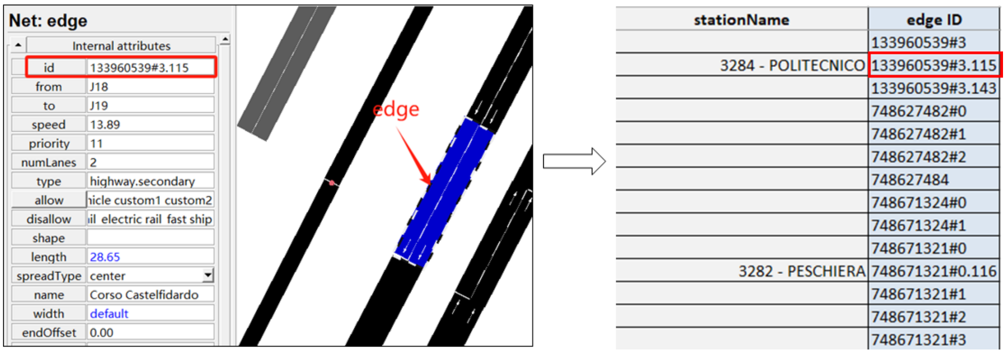


Figure 3.10: Bus Route Representation in MATLAB

regards to the road network's inability to incorporate altitude information, which is a critical factor in determining road slope. But in the case of this Master's Thesis it is not significant, because the focus is a small urban area that has little elevation changes along the road network used by the BEBs. Besides, it is also important to recognize that temperature data, although provided by the user, is greatly simplified, with a single temperature value applied uniformly throughout the entire map, a simplification that has been commonly employed in previous studies, but nonetheless warrants further refinement for more precise results [59][60].

3.3.3 Bus Schedule

In this Master's thesis, the bus schedule plays a crucial role as a critical constraint that significantly impacts our optimization objective. Specifically, we define the bus schedule in accordance with the information gleaned from the GTT website [58]. The bus schedule essentially outlines the precise timing and frequency of bus departures and arrivals at specific stops situated along a designated route.

Bus Line	Trip Direction	First Trip Time	Last Trip Time	Number of Trips
Bus Line 12	$T_A \rightarrow T_B$	5:00	21:12	61
	$T_B \rightarrow T_A$	4:50	21:00	62
Bus Line 58	$T_B \rightarrow T_C$	4:50	21:05	74
	$T_C \rightarrow T_B$	5:00	21:00	73

Table 3.3: Bus Schedule

In table 3.3, we define the first trip time, the last trip time and the number of trips of each bus line. The detailed schedules are shown in Table A.1 to Table A.4, in Appendix A.

3.3.4 Passenger Car Traffic Flow

Vehicle flow, also known as traffic flow, refers to the rate at which vehicles travel through a specific section of roadway over a given period of time [61]. It is typically expressed as the number of vehicles passing a particular point per unit time, often measured in vehicles per hour.

As previously stated, the vehicle flow on the road significantly impacts various aspects of bus operations, including dwell time at stops, dynamic behavior, and energy consumption. In this Master's thesis, we incorporate vehicle flow into the construction of the driving cycle to accurately capture its influence on these factors. By accounting for vehicle flow during the development of the driving cycle, we aim to provide a more accurate bus operations that considers real-world traffic conditions and their implications on bus performance and efficiency.

In the SUMO environment, it is feasible to define repeated vehicle flows, which share the same parameters as individual vehicle or trip definitions except for the departure time [55]. The vehicle flow we create is illustrated in Figure 3.11.

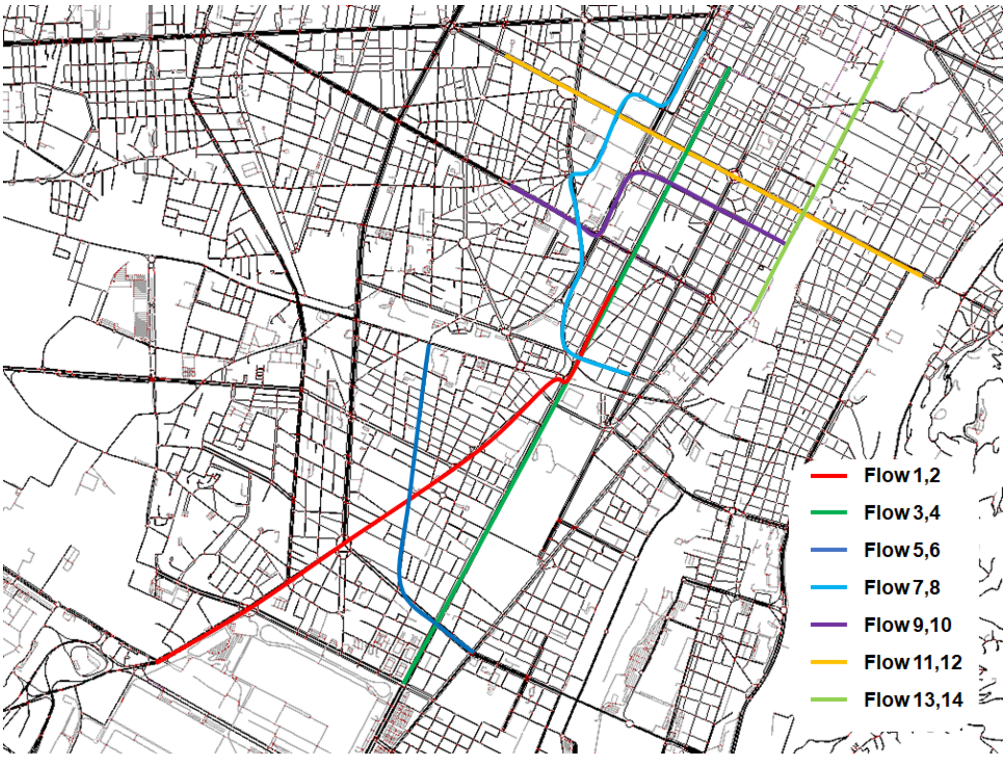


Figure 3.11: Passenger Car Traffic Flows

Traffic flow exhibits temporal variations throughout the day due to changing travel demands and external factors such as weather and road conditions. This phenomenon has been extensively studied in transportation research. For instance, in a literature, the work on nonlinear effects in car-following dynamics, both highlight the temporal dynamics of traffic flow and its implications for transportation system management and planning [62].

To accurately represent the varying vehicle flow throughout the day, it's essential to assign distinct values to each vehicle flow defined in the SUMO environment. In this Master's thesis, we utilize seven distinct values, which is illustrated in Table 3.4, to establish different vehicle flows. This approach ensures that the simulated traffic patterns align with the temporal dynamics observed in real-world traffic conditions.

Time of One Day	Passenger Car Traffic Flow (vehicles/hour)
0:00-5:00	30
5:00-7:00	50
7:00-9:00	100
9:00-16:00	70
16:00-19:00	90
19:00-21:00	70
21:00-24:00	40

Table 3.4: Passenger Car Traffic Flow of One Day

3.3.5 Driving Cycles Building

In the preceding sections, we have delineated and examined the details of the road network, as well as the bus lines, encompassing its designated route and corresponding stops, in addition to the bus schedule, which outlines the precise timings of departures and frequency, and finally, the vehicle flow, which represents the movement and circulation of vehicles throughout the road network.

Starting from the network previously described, it is possible to build routes for the "*terminal* $\rightarrow$ *terminal*" operation, as presented in Algorithm 1.

The construction of driving cycle for buses has the goal to obtain their speed and acceleration profiles from SUMO simulation, input necessary for the Cost Table Building phase.

Algorithm 1 Algorithm to Build Driving Cycle

Connect to SUMO Environment
Load Road Network ▷ Including vehicle flows
Load bus route
Load bus schedule for "Line 12 Sud"
Load bus schedule for "Line 12 Nord"
Load bus schedule for "Line 58 Sud"
Load bus schedule for "Line 58 Nord"
Create variables to save driving cycle
define bus id i, j, k, n for each bus line
while True **do**
    Perform a simulation step in the SUMO server
    Returns the current simulation time
    if non-arrived vehicles is Zero **then**
        Break
    end if
    if Current time is in bus schedule for "Line 12 Sud" **then**
        Bus_i: Departure from T_A, Trip: $T_A \rightarrow T_B$
        i = i + 1
    end if
    if Current time is in bus schedule for "Line 12 Nord" **then**
        Bus_j: Departure from T_B, Trip: $T_B \rightarrow T_A$
        j = j + 1
    end if
    if Current time is in bus schedule for "Line 58 Sud" **then**
        Bus_k: Departure from T_C, Trip: $T_C \rightarrow T_B$
        k = k + 1
    end if
    if Current time is in bus schedule for "Line 58 Nord" **then**
        Bus_n: Departure from T_B, Trip: $T_B \rightarrow T_C$
        n = n + 1
    end if
    Save the driving cycle data of all buses ▷ Including time, velocity, acceleration and position
end while

3.4 Cost Table Building

The second step followed in the methodology is the definition of a cost table presenting the energy required to perform a travel on any line considered at any time slot. It is however important to point out that the SOC itself heavily influences such requirements, at least at battery level, since it is a variable affecting the internal resistance of the battery and therefore the overall efficiency of the bus. For instance, a BEB with a 90% SOC will exhibit a different variation in SOC changes compared to another BEB with a 60% SOC when performing the same trip. Therefore, it is imperative that we take into account the influence of SOC on energy consumption.

In our study, we have constrained the working range of SOC of BEBs to between 20% and 95%. For computational reasons, this interval was discretized into 15 equispaced levels of starting SOC. As every BEB trip yields an overall battery depletion, the lowest SOC for which energy requirements are computed is 25%, as no bus with SOC as low as 20% can actually begin a mission.

The number of passengers on BEBs also has a significant impact on the overall energy consumption. However, it is not practical to incorporate all the possible scenarios and situations into our cost table, as there are numerous variables at play. Therefore, in order to build our cost table, we have opted to utilize fixed passenger numbers. The influence of these passengers will be further validated and confirmed in Section 3.6, which is dedicated to the validation process. In the context of this particular study, we have chosen to utilize 70% of the total passenger capacity of the BEB to construct the cost table.

In our cost table, we have incorporated six distinct parameters of content for each individual trip:

- The first parameter pertains to the start time of the trip, denoted by the time of day measured in minutes, which is directly derived from the bus schedule, thereby ensuring that the timing of each trip is accurately captured.

- The second parameter involves the length of the route, calculated in kilometers, which is integrated from the driving cycle that we have built from SUMO simulation, thereby providing a precise measurement of the distance traversed during each trip.

- The third parameter comprises the energy consumption, expressed in kilowatt-hours, which is simulated from the BEB model that we have constructed, taking into account the various factors that influence energy consumption.

- The fourth parameter entails the specific consumption, measured in kilowatt-hours per kilometer, which is calculated by dividing the energy consumption by the length of the route, thereby providing a indicator of the energy efficiency of each trip, and enabling the identification of opportunities for improvement.
- The fifth parameter corresponds to the trip duration, quantified in minutes, which is directly derived from the driving cycle, thereby providing a detailed understanding of the time taken to complete each trip.
- The sixth and final parameter involves the end time of the trip, denoted by the time of day measured in minutes, which is calculated by adding the trip duration to the start time of the trip, thereby providing a complete and accurate picture of each trip.

We construct our cost table by utilizing the script outlined in Algorithm 2, which provides a detailed and step-by-step guide for building this table.

Algorithm 2 Algorithm to Build Cost Table

```
Load BEB parameters
Load driving cycle
Load bus schedule
Initial SOC table
Set numbers of passengers
for i = 1: number of trips do
    for j = 1: number of Initial SOC do
        SOC = SOCTable(j)
        for k = 1: time steps of driving cycle do
            SOC(k+1) = BEBModel(SOC(k),DrivingCycle.Velocity,
DrivingCycle.Acceleration, BEB Parameters, Passengers)
        end for
    end for
    CostTable(i,1,j): Start Time of Trip
    CostTable(i,2,j): Length of Trip
    CostTable(i,3,j): Energy Consumption of Trip
    CostTable(i,4,j): Specific Consumption of Trip
    CostTable(i,5,j): Duration of Trip
    CostTable(i,6,j): End Time of Trip
end for
Save cost table
```

3.5 Optimization

The primary objective of this Master's Thesis is to effectively plan the charging activity for BEB fleets with the aim of minimizing two crucial aspects: the total number of BEBs, and the overall cost incurred to recharge all the BEBs within a single day.

To achieve this goal, we will initially organize our objective into a objective function. Subsequently, we will define the constraints that govern our objective function, ensuring that all necessary parameters are taken into account. Finally, we will design and develop an optimization algorithm capable of solving our complex objective function.

Now, let us explore each section in greater detail, providing a thorough examination of the methodologies and techniques employed to achieve our objectives.

3.5.1 Objective Function

The proposed planning of recharging for BEB fleets problem is to minimize the total number of BEBs and charging cost by determining whether a particular BEB from the fleet should be charged or not at a specific time interval during an operational day. This decision-making process necessitates the simultaneous consideration of multiple crucial factors, including the bus schedule, TOU tariffs, the occupation status of charging stations, the limitations imposed by the SOC of the BEBs, and the energy consumption. In order to facilitate a more in-depth discussion of this multifaceted problem, the notation employed in the objective function is outlined in Table 3.5, providing a reference point for further analysis and exploration.

Notation	**Explanation**
N	The number of BEBs
$p_{BEB,n}$	The price to purchase BEB n
$q_{e,BEB,n}$	The amount of electricity charged into BEB n
$p_{e,t}$	The electricity price of a charging time t
α	Weight factor accounting for BEB price

Table 3.5: Notations used in Objective Function

Following the above notation, a mathematical objective function for the proposed charging scheduling problem is formulated.

$$obj = min \sum_{n=1}^{N} (p_{BEB,n} * \alpha + (q_{e,BEB,n} * p_{e,t}) * (1 - \alpha)) \tag{3.19}$$

3.5.2 Constraints

To address the objective function, we will identify and emphasize the essential features of the proposed problem, then explain and elaborate on the key factors and constraints that have been considered and integrated into the optimization process.

BEBs Configuration

All BEBs considered in the simulation are assumed to be of a single model, therefore their parameters are the same.

Bus Operation Rules

First, all the BEBs initiate their daily operational routine by departing from the designated depot, and subsequently, upon completion of all their assigned tasks, they return to the very same depot, marking the end of their daily cycle.

Second, it is a fundamental characteristic of all BEBs, that they are exclusively designed to operate on a predetermined and fixed bus route, which means that if a particular BEB is assigned to operate on bus line number 12 on a given day, it is not feasible for it to operate on a different bus line, such as bus line number 58, on that same day, and this rigid assignment of bus lines applies universally to all BEBs in the fleet.

Third, it is imperative that the bus schedule is strictly adhered to and implemented with precision, which means that at each and every designated time slot, as outlined in the bus schedule, there must be exactly one BEB, that is assigned to perform the task, ensuring that the transportation service runs smoothly and efficiently.

Fourth, it is crucial to acknowledge that the battery serves as the sole energy source that powers the BEB. Consequently, the driving range of the BEB is inherently limited by the capacity of its battery. As a result, it may not be feasible for the BEB to accomplish its daily tasks without the necessity of recharging its battery. In order to effectively address this issue, it is imperative that we implement a strategy of recharging the BEB during periods of inactivity, specifically when it is waiting for its next task at the terminal, thereby ensuring that the BEB is always adequately powered to perform its duties.

SOC Operational Range

The operational range of the SOC of all BEBs is specifically defined as being within a certain limited scope, namely from a minimum of 20% to a maximum of 95%. In other words, it is crucial to emphasize that the SOC of each and every individual BEB cannot, under any circumstances, fall below the predetermined threshold of 20% at any point throughout the entire day, and similarly, the SOC of each BEB cannot be charged to a level that exceeds the maximum capacity of 95%.

Additionally, it is worth noting that the SOC of all BEBs is always at its maximum capacity of 95% when they initially depart from the depot, thereby ensuring that they are ready for operation. Furthermore, it is absolutely essential to highlight that after a full night of charging, the SOC of all BEBs must necessarily return to its maximum capacity of 95%, thereby guaranteeing that they are fully charged and ready for operation on the following day.

Charging Stations

There exist two categories of charging stations, specifically the terminal charging station and the depot charging station, each with its unique characteristics and purposes. As the name explicitly suggests, the terminal charging station is strategically constructed in close proximity to the terminal of the bus line, thereby facilitating efficient charging operations. On the other hand, the depot charging stations are situated inside the bus depot, catering to the specific needs of the BEBs.

In the context of the terminal charging station, their primary function is to recharge the BEBs subsequent to the completion of one trip, when the bus comes to a halt at the terminal and awaits its next assignment. It is essential to note that the process of charging one BEB is a time-consuming endeavor, rendering it impractical to utilize slow chargers for this purpose. Consequently, all terminal charging stations are equipped with fast chargers, which are capable of delivering a significantly higher power output. In the scope of this Master's thesis, we have defined the power output of the fast charger to be 160 kW.

With regard to the depot charging station, their primary objective is to recharge the BEBs subsequent to the completion of their daily tasks, upon their return to the depot. It is crucial to acknowledge that the power output of the charger has a profound impact on the lifespan of the battery, and the simultaneous charging of multiple BEBs can exert a significant influence on the power grid. Therefore, all depot charger power outputs are deliberately limited to 90 kW, thereby ensuring a more controlled and sustainable charging process.

Electricity Load Capacity

The electricity load capacity of charging stations assumes a crucial role in determining optimal charging schedules, as extensively discussed in various studies [63][64][65]. When considering the spatial constraints of a charging station, it becomes apparent that the maximum number of electric buses that can be charged simultaneously is strictly limited by the total parking space available, which in turn has a direct impact on the overall capacity of the station [66]. Furthermore, from the perspective of the local power grid, the maximum charging power of all chargers is inherently restricted by the capability of electricity distribution systems, which can only handle a certain amount of power before becoming overwhelmed [63][64][65]. In today's scenario, it is still necessary to undertake costly and time-consuming upgrades to the charging power systems in order to support substantial electricity demand, which can be a significant burden on resources [67]. When a cluster of electric buses is charged simultaneously at a charging station, it can trigger a charging power surge in the local power grid, leading to a multitude of negative consequences, including transformer overload, voltage quality deterioration, and wire damage, all of which can have far-reaching and devastating effects.

Therefore, it is essential to exercise control over the total charging load of a charging station, ensuring that it remains within a predetermined bound to prevent any adverse effects on the power grid. In reality, the electricity load capacity has a profound influence on the charging schedule of the electric bus fleet, which tends to disperse the intensive charging from the off-peak periods to on-peak periods that have a higher electricity rate, thereby optimizing the overall charging process and minimizing its impact on the power grid.

In this Master's Thesis, we control the electricity load capacity by constraining the number of charger. The detailed number of chargers utilized is shown in Table 3.6.

Position	**Number of chargers**	**Power**
T_A	1	160 kW
T_B	2	160 kW
T_C	1	160 kW
Depot	4	90 kW

Table 3.6: Details of Chargers

Charging Duration

Many studies have shown that fast charging can accelerate battery aging, leading to significant capacity and power fade while posing an unacceptable safety hazard during operation [68]. Therefore, to reduce the times needed to charge BEBs, the duration of fast charging should not be too short. On the other hand, Battery Electric Buses (BEBs) must complete their assigned tasks, so the duration of fast charging should not be excessively long either. In this thesis, we set the fast charge duration to 20 minutes.

For slow charging at depot charge stations, the charge duration is determined by the time needed to charge the BEBs to their maximum State of Charge (SOC).

Energy Consumption

Energy consumption is an extremely crucial factor that significantly influences the precision and reliability of estimating the SOC of one BEB. As we have previously discussed in the preceding section, we have successfully constructed the cost table that contains the detailed information regarding the energy consumption of each and every trip, as well as that of each bus line. This approach is the main novelty with respect to methods present in literature, which have traditionally relied on using a fixed energy consumption value that lacks accuracy and flexibility.

In order to effectively extract the energy consumption value from our cost table, we have developed a specialized MATLAB function. The input parameters of this function comprise the time of the bus schedule, the SOC of the battery of the BEB, and the cost table response specifically tailored to the bus line in question. The output of this function is e_{con} (kWh), the energy consumption of the exact trip of the BEB at the exact time and with the exact SOC, thereby providing a highly accurate and reliable estimation of the energy consumption.

Trip Time Duration

The time duration of a trip, which is another important aspect of this research, is a state-of-the-art concept that has been explored in this thesis. In contrast to other studies, which have relied on the constant trip time [25][26][27]. Our approach recognizes the limitations of this method and its lack of accuracy. And, our study takes into account the significant impact of traffic conditions and vehicle flows on trip time duration, which are essential factors that cannot be overlooked.

The methodology employed to determine trip duration is analogous to the approach used to extract energy consumption.

Electricity TOU tariffs

The significance of TOU tariffs has been extensively acknowledged as a crucial factor to be taken into account in the charging scheduling decisions of the BEB fleets, as highlighted in various studies [67]. The TOU tariffs are specifically designed to encourage users to consume electricity during the off-peak periods by setting a higher electricity rate during the on-peak periods, rather than using a single uniform electricity rate throughout the day.

When TOU tariffs are implemented, the charging price during on-peak periods can be significantly higher, than that of off-peak periods [69]. This means that the electricity cost of BEBs is highly dependent on their charging profiles. It is a well-established fact that the TOU tariffs can have a profound impact on the charging activity pattern of the BEB fleet, influencing the way they operate and recharge [27]. As a result, frequent charging during on-peak periods would be largely avoided, since it would substantially increase the electric bus charging cost, thereby compromising the economic viability and attractiveness of electric buses as a sustainable transportation option.

In this Master's Thesis, the details of TOU tariffs are shown in Table 3.7.

Time of Day	**Electricity Price (€/kWh)**
0:00 - 8:00	0.25
8:00 - 19:00	0.3
19:00 - 24:00	0.25

Table 3.7: TOU Tariffs of Electricity

3.5.3 Optimization Algorithm

Up to this point, we have prepared all the necessary inputs required to solve the objective function. Therefore, in the subsequent step, our primary focus will shift to the design and development of the optimization algorithm.

The algorithm, shown in Algorithm 3, is designed to optimize the recharging plan for fleets of BEBs. The goal is to minimize the objective function, which is related to the cost of BEBs and electricity recharged to battery.

Step-by-Step Explanation

Algorithm 3 Algorithm to Planning of Recharging BEB Fleets

```
Load cost tables
Load constraints
Define start time for fast charging (fchgtime)
Define Variables to save data
Set optimal value of objective function to inf
for t == time of day (in minute) do
    busmin12 = Function to determine the min number of BEBs to perform task of bus line 12 without charging
    busmin58 = Function to determine the min number of BEBs to perform task of bus line 58 without charging
end for
busnum12 = busmin12
busnum58 = busmin58
for i = 1:numel(fchgtime) do
    start fast charging time == fchgtime(i)
    for t == time of day (in minute) do
        Defined function to perform bus schedule of line 12
        Defined function to charge BEBs of bus line 12 (fast charging)
        Defined function to perform bus schedule of line 58
        Defined function to charge BEBs of bus line 58 (fast charging)
        BEBs return to terminal after finishing fast charging
        BEBs return to depot after all tasks
        Defined function to perform depot charging
        Calculate electricity charged to each BEB
        Calculate the value of objective function
        if Calculated value < Optimal value then
            Optimal value = Calculated value
            Optimal plan = BEB fleet daily activity
        end if
    end for
    if Bus line 12 is not feasible then
        busnum12 = busnum12 + 1
    end if
    if Bus line 58 is not feasible then
        busnum58 = busnum58 + 1
    end if
end for
```

- Load Cost Tables and Constraints: The algorithm starts by loading cost tables and constraints, which are related to the cost of electricity, bus schedules, and charging station capacities.
- Define Start Time for Fast Charging: The algorithm defines the start time for fast charging, which is stored in an array fchgtime.
- Define Variables to Save Data: The algorithm defines variables to save data, which will be used to store the results of the optimization process.
- Set Optimal Value of Objective Function to Infinity: The algorithm initializes the optimal value of the objective function to infinity, which will be updated as the algorithm iterates.
- Determine the minimum number of BEBs to perform task of bus line 12 and bus line 58 without charging.
- Set initial number of BEBs for bus fleet of line 12 and line 58 to these two minimum value.
- Main Loop. The algorithm iterates over each possible start time for fast charging (fchgtime(i)). For each iteration:
  - Set Start Fast Charging Time: The algorithm sets the start time for fast charging to fchgtime(i).
  - Perform Bus Schedule for Line 12 and 58: The algorithm defines functions to perform bus schedules for lines 12 and 58.
  - Perform fast charging for BEBs of bus line 12 and bus line 58.
  - BEB Returns to Terminal and Depot: The algorithm simulates the BEBs returning to the terminal after finishing fast charging and then returning to the depot after completing all tasks.
  - Perform Depot Charging: The algorithm defines a function to perform depot charging.
  - Calculate Electricity Charged to Each BEB: The algorithm calculates the amount of electricity charged to each BEB.
  - Calculate Objective Function Value: The algorithm calculates the value of the objective function.
  - Update Optimal Value and Plan: If the calculated value is less than the current optimal value, the algorithm updates the optimal value and saves the corresponding BEB fleet daily activity plan.
  - If not feasible of bus line 12, the number of BEBs of bus line 12 plus one, then restart the main loop.

  - If not feasible of bus line 58, the number of BEBs pg bus line 58 plus one, then restart the main loop.

- Termination. The algorithm terminates after iterating over all possible start times for fast charging.

In summary, this algorithm is designed to optimize the recharging plan for a fleet of BEBs by iteratively evaluating different start times for fast charging and selecting the plan that minimizes the objective function.

3.6 Validation

This is the final section of our methodology, where we validate the results which come from the optimization algorithm, specifically designed to yield the optimal charging plan for our BEB fleets. It is important to repeat a crucial aspect that was previously mentioned, namely, the assumption of a fixed number of passengers during the construction of our cost table. However, in real-world scenarios, this assumption is unrealistic, and thus, in this section, we must carefully examine the impact of the number of passengers on our overall strategy.

To effectively incorporate the number of passengers into our calculations, we must dynamically adjust the number of passengers on each BEB.

In the preceding section, we successfully obtained the optimal result of the objective function, which encompasses the minimum cost of the total cost of BEBs and the total cost to charge the BEBs, as well as the daily activity of each BEB. In other words, we have determined the precise number of BEBs required to fulfill the bus schedule of each bus line and the specific tasks and charging activities performed by each BEB. Building upon this foundation, we can now modify the number of passengers on each BEB and conduct a detailed vehicle simulation for each trip undertaken by the BEB, thereby ensuring a more accurate and realistic representation of our optimal result.

3.6.1 Number of Passengers on BEBs

It is acknowledged that the number of passengers on a BEB exhibits a complex dependence on multiple factors, including not only the time of day but also the specific stop along the bus line, and accurately determining the exact number of passengers on a BEB at any given time is a challenging task. In lectures, many efforts have been made to predict passenger flow [70][71]. The authors find that the passenger flow changes in a day in a bimodal pattern, with obvious morning and evening peak in [72]. The morning peak on weekdays is about 7:00-9:00, and the evening peak is 17:00-19:00.

In the context of this Master's thesis, we propose a model where the number of passengers on a BEB is solely dependent on the time of day. To illustrate this concept more clearly, let us consider a specific example. Suppose a BEB is scheduled to perform a trip at 9:00 am, in this particular scenario, we will maintain a constant number of passengers throughout the entire duration of that trip. However, if the same BEB is scheduled to perform another trip at 11:00 am, we will intentionally alter the number of passengers on the BEB.

In order to simulate the changes in passenger numbers, we will employ a random value that falls within a predetermined range, shown in table 3.8.

Time of day	Passengers(% of Capacity)
before 6:00	10% - 30%
6:00 - 7:00	30% - 60%
7:00 - 9:00	70% - 100%
9:00 - 16:00	40% - 80%
16:00 - 20:00	70% - 100%
20:00 - 21:00	50% - 80%
after 21:00	30% - 60%

Table 3.8: Passengers on BEB Depend on Time of Day

We can utilize this information to determine the number of passengers that were on the BEB during a specific trip. This can be accomplished by examining the starting and ending terminal of the trip, which we have previously recorded as part of our optimal charging plan.

Figure 3.12 and Figure 3.13 represent the number of passengers on each BEB at specific trip that BEB operate.

The x-axis represents the time of day, ranging from early morning to late evening. The y-axis indicates the number of passengers, with values ranging from 0 to 90. Each subplot displays the passengers at different time for a specific BEB.

Both figures show significant variation in passenger numbers throughout the day, reflecting the dynamic nature of public transportation demand. Peaks in passenger counts can be observed during morning and evening rush hours in both figures, which is typical for urban bus lines.

Each bus exhibits unique patterns of passenger count variations, influenced by factors such as route segments, time of day, and specific stops. Comparing individual buses across both figures reveals that some buses might have higher peak loads than others, indicating different levels of demand on different routes and time.

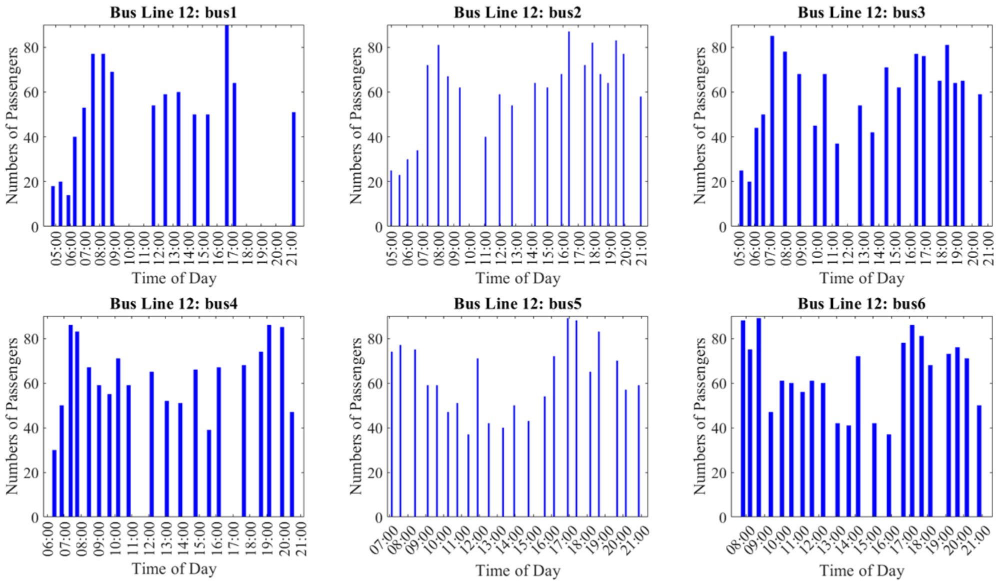


Figure 3.12: Number of Passengers on BEBs for Bus Line 12

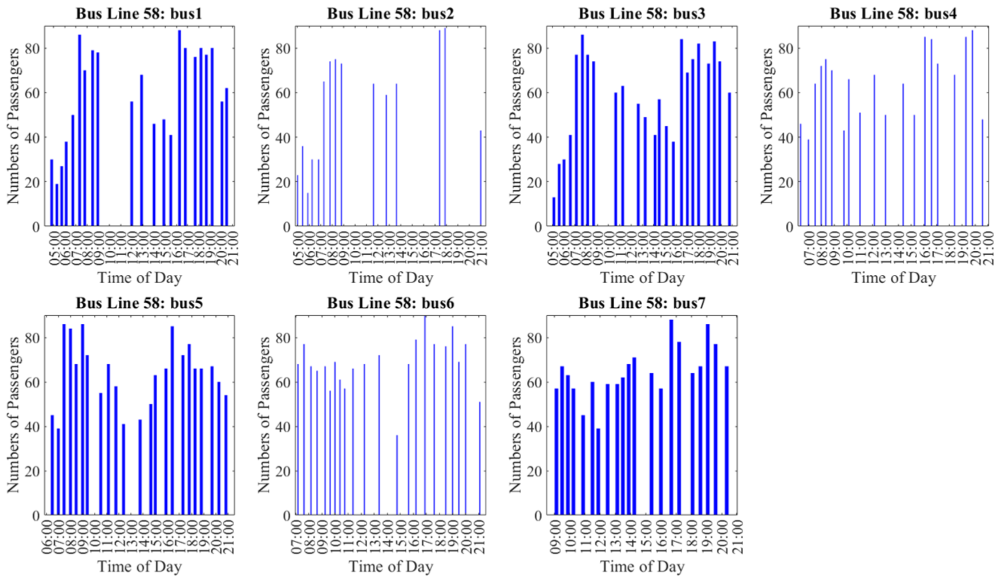


Figure 3.13: Number of Passengers on BEBs for Bus Line 58

3.6.2 Validate the Charging Plan

If the BEB is in the process of performing its assigned tasks according to the predetermined bus schedule, we can estimate the number of passengers on board by referencing a random value found in Table 3.8, which depends on the time of the trip. In any scenario where the BEB was not engaged in any of bus schedules, we can assume that there were zero passengers on board. The step-by-step script used to validate this process is outlined in detail in Algorithm 4, which provides a guide for implementation.

Algorithm 4 Algorithm to Validate Optimal Recharging Plan

```
Load optimal recharging plan     ▷ Include all the activity performed by BEB
Load cost tables
Load driving cycles
Load BEB parameters
for i = 1 : number of BEBs do
    Get the data stored in optimal recharging plan of BEB(i)
    Set initial SOC of BEB(i) to 95% ▷ Every BEB start trip from depot with maximum SOC
    for j = 1: number of activity of BEB(i) do
        if BEB is discharging then
            if BEB perform task in bus schedule then
                Decide the number of passengers according to table 3.8
            else
                The number of passengers is zero
            end if
            Select the driving cycle we have constructed in Section 3.3
            for k = 1: time steps of driving cycle do
                SOC(k+1) = BEBModel(SOC(k),DrivingCycle.Velocity, DrivingCycle.Acceleration, BEB Parameters, Passengers)
            end for
        else
            if day time charging then
                Perform day time charging
            else
                Perform night charging
            end if
        end if
        Save the data of one activity
    end for
    Save the data of all activity
end for
```

Chapter 4

Results

In this chapter, we are going to provide a comprehensive overview of the outcome that we have achieved throughout our entire project. In accordance with the step-by-step process of our work, initially, we will conduct a thorough examination and in-depth analysis of the driving cycle data that we obtained from our SUMO simulation, which was discussed in detail in Section 3.3. Subsequently, we will explore the cost table that we constructed in Section 3.4, which serves as a crucial component of our project. Following that, we will present the optimal charging plan that we derived from our sophisticated optimization algorithm, which was elaborated upon in Section 3.5. Lastly, we will display the validation results, which will provide conclusive evidence of the effectiveness of our approach.

4.1 Driving Cycle Analysis

In this particular section of our analysis, we will provide an in-depth examination of the driving cycle associated to the trip that is explicitly included in the bus schedule. It is essential to note that, within the scope of our project, we are dealing with two distinct bus lines, each of which has been further subdivided into two distinct parts, namely, $South \rightarrow North$ and $North \rightarrow South$. As a result, for each individual trip, we have successfully constructed a unique driving cycle. In total, we have built 456 driving cycles, with each one corresponding precisely to one specific bus schedule.

Moving forward, we will start a thorough discussion of the significant influence exerted by traffic conditions on the driving cycle. Subsequently, we will undertake a comparison of the driving cycle between different bus lines. Finally, we will conduct a comparison between a driving cycle obtained in our work and the Manhattan Bus Cycle, which is a widely recognized chassis dynamometer test specifically designed for urban buses.

4.1.1 Influence of Traffic Conditions to Driving Cycle

Firstly, we constructed driving cycles with traffic flow and, conversely, without vehicle flow. This enables us to compare the driving cycle of the same bus schedule time within the same bus line. Secondly, within the driving cycle built with traffic flow, we can undertake a comparative analysis of the driving cycle of different bus schedule times within the same bus line.

Comparison of driving cycle built with and without traffic flow

The Figure 4.1 illustrates a line graph that provides the velocity of a bus operating with and without the presence of traffic flow. The graphical representation is plotted against time, with the x-axis denoting the trip time in minutes and the y-axis denoting the velocity in kilometers per hour. The black line on the graph corresponds to the velocity of the bus when operating with traffic flow, whereas the red line represents the velocity of the bus when operating without traffic flow.

A closer examination of the graph reveals that the most notable distinction between the two driving cycles is the significant difference in trip time. The trip time of the driving cycle constructed with vehicle flow is appreciably longer than that of the driving cycle without vehicle flow. This disparity is evident not only in the overall trip time but also in the velocity at every instant, with the exception of the initial few minutes of the trip. The velocity profiles of the two driving

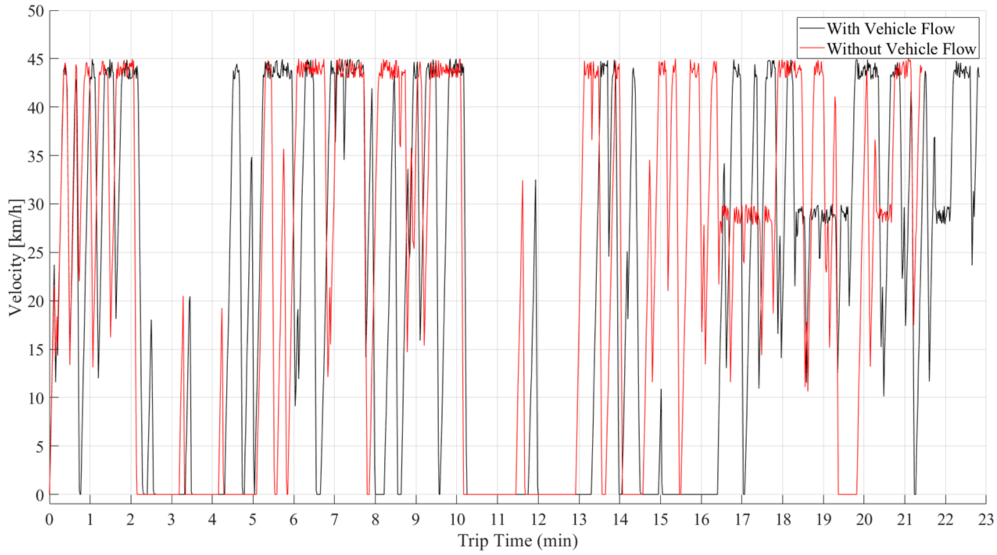


Figure 4.1: Driving Cycle Built with and without Traffic Flow

cycles exhibit a marked difference, indicating that the presence of traffic flow has a significant impact on the driving cycle of buses operating in urban cities.

It is worth noting that the incorporation of traffic flow into the driving cycle results in a more realistic representation of the actual operating conditions of buses in urban environments. Therefore, in the subsequent sections of this study, all results and findings will be based on the driving cycles constructed with traffic flow, which provides a more accurate and reliable representation of the actual operating conditions of buses in urban cities.

Comparison of driving cycle of different bus schedule time

As depicted in Figure 4.2, we have undertaken a comparison of the driving cycles corresponding to four distinct bus schedule times, specifically 5:00, 6:03, 7:07, and 8:12. A thorough examination of the graph reveals that the trip time of each of these four driving cycles exhibits notable differences.

One of the primary reasons underlying these discrepancies is the fact that we employed different vehicle flow during these time ranges as we have presented in Section 3.3. However, it is also worth noting that even when we utilized the same vehicle flow in constructing the driving cycles of the blue line and green line, the trip time still exhibited significant variations.

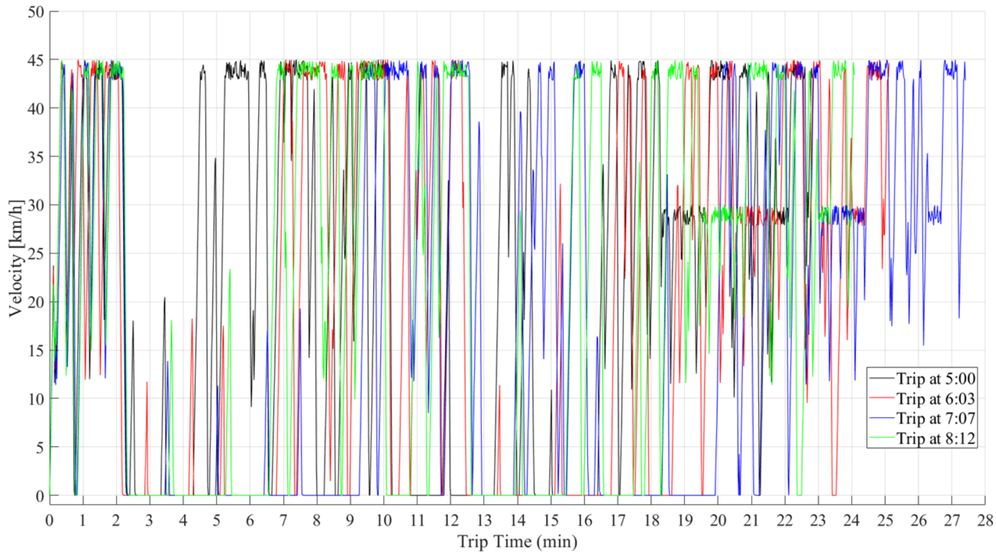


Figure 4.2: Driving Cycle of Bus Line 12 ($North \rightarrow South$) at Different Time

Another crucial factor contributing to these differences is the traffic light conditions. Specifically, buses scheduled to operate at different times of the day will inevitably encounter distinct traffic light conditions and vehicle flow conditions, thereby resulting in unique driving cycles for each specific bus trip. Consequently, within the scope of this project, we have constructed specific driving cycles for each scheduled bus trip.

4.1.2 Comparison of Driving Cycle Between Different Bus Line

As depicted in Figure 4.3, the disparities are not limited to the trip time alone, but also encompass the behavior of the bus during the trip. This is attributable to the fact that the length of the bus route, the traffic light conditions, and the vehicle flow conditions are all unique to each bus line. Consequently, it is imperative to construct driving cycles that are tailored to each specific bus line and bus schedule, as we have successfully accomplished in this project.

The differences in the driving cycles of the two bus lines are a direct result of the varying operating conditions that each bus line encounters. The bus route length, for instance, has a significant impact on the trip time, with longer routes inevitably resulting in longer trip times. Furthermore, the traffic light conditions along the route also play a crucial role in shaping the driving cycle, as buses are forced to decelerate and accelerate in response to the changing traffic light signals.

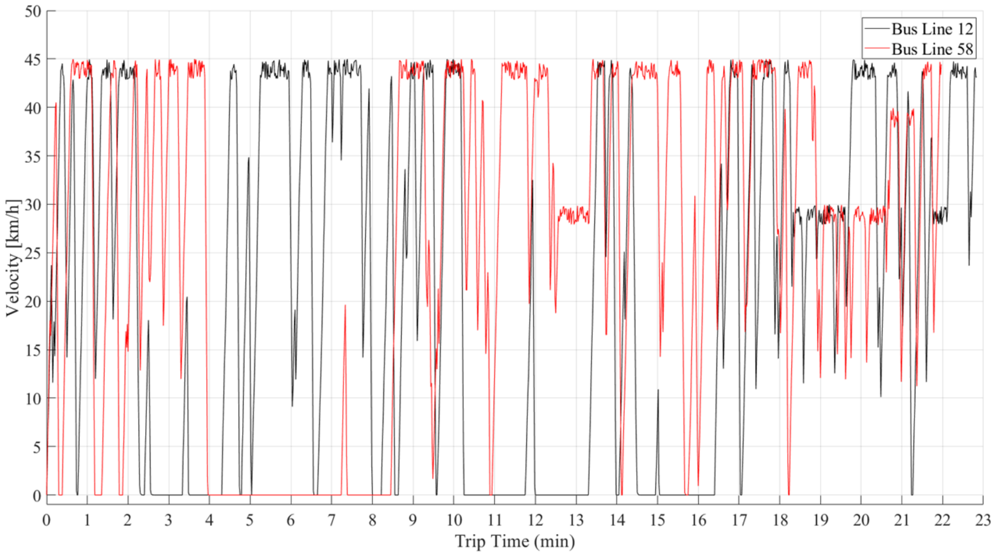


Figure 4.3: Driving Cycle of Different Bus Line

Additionally, the vehicle flow conditions, which are influenced by factors such as time of day, road network, and traffic volume, also contribute to the distinct driving cycles of each bus line.

In light of these differences, it is essential to adopt an approach to driving cycle construction, one that takes into account the unique characteristics of each bus line and bus schedule. By doing so, we can ensure that the driving cycles accurately reflect the real-world operating conditions of each bus line, thereby facilitating more effective and efficient bus operations

4.2 Cost Table Analysis

As we have previously explained in considerable details, our cost table encompasses six distinct parameters for each individual trip, thereby providing a comprehensive and detailed analysis of the various parameters that influence the operation of our BEB fleet. Moreover, we have taken the crucial step of incorporating the initial SOC of each trip into our calculations, thereby acknowledging the significant impact that SOC has on the overall performance of our BEB fleet. Consequently, our cost table assumes a three-dimensional structure, with the additional dimension of SOC providing a more accurate understanding of the complex interplay between the various factors that influence the operation of our BEB fleet.

In the subsequent sections of this report, we will engage in a discussion of the length of the trip, the specific consumption, and the trip duration, that influence the operation of our BEB fleet. Specifically, in the section dedicated to the specific consumption, we will dive into the influence of SOC on specific consumption, examining the ways in which variations in SOC impact energy consumption and efficiency, and exploring the implications of these findings for the following optimization part.

4.2.1 Consistency in Length of Route Calculated

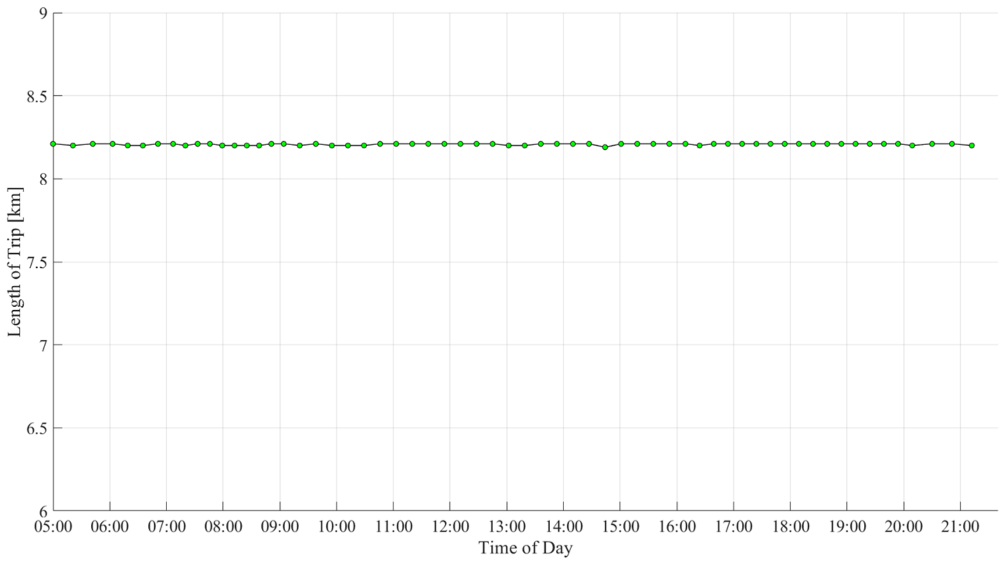


Figure 4.4: Length Calculated of Bus Line 12 ($North \rightarrow South$)

As depicted in Figure 4.4, we undertook a calculation of the length of the route for bus line 12, traversing from Nord to Sud, for each of the scheduled trips. Although the calculated values exhibit a degree of fluctuation, it is noteworthy that the error margin between these values and the actual values remains remarkably low, falling within a narrow range of 0.5%.

The results unequivocally demonstrate that our methodology for generating driving cycles via SUMO simulation is reliable, reproducible, and capable of producing outcomes that closely align with real-world data. By leveraging the strengths of SUMO simulation, we have been able to create a robust and dependable framework for generating driving cycles that accurately capture the complexities of real-world bus operations.

4.2.2 Stochasticity of Trip Duration

In the real-world transit operation of BEBs, the actual travel times are inherently characterized by fluctuations around the scheduled travel times, primarily due to the interference from multiple stochastic factors, including, but not limited to, road vehicle flow states, traffic light states, queuing status at intersections, and passenger flows at stations. These factors, which are inherently unpredictable and subject to variations, contribute to the variability in travel times, making it challenging to establish fixed travel times.

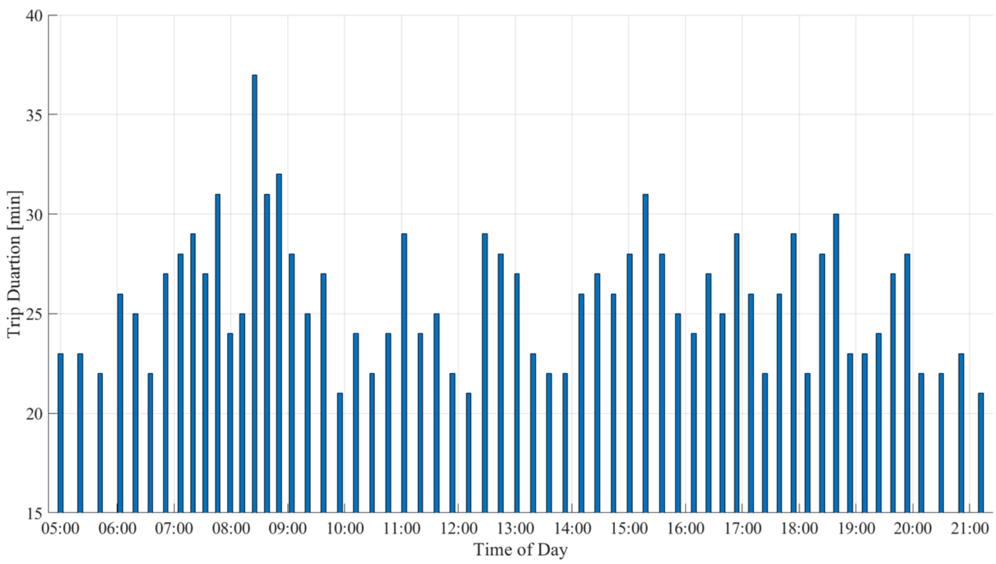


Figure 4.5: Trip Duration of Bus Line 12 ($North \rightarrow South$)

In Figure 4.5, the trip duration exhibits notable differences from one another, despite the fact that they perform the same bus route. This phenomenon can be attributed to the fact that, in the process of building the driving cycle, we have taken into account the vehicle flow and simulated the traffic light states in the SUMO environment, thereby incorporating the complexities and uncertainties of real-world traffic conditions.

Consequently, the driving cycle obtained by our method can be considered a more accurate and reliable representation of actual bus operation tooling, enabling the estimation of energy consumption that is more precise and reflective of real-world conditions. By acknowledging and incorporating the stochastic nature of bus operations, our approach provides a more deep understanding of the underlying factors that influence energy consumption, ultimately facilitating the development of more effective and efficient recharging plan of the BEB fleets.

4.2.3 Specific Consumption

The specific consumption is a very important factor in our optimization problem, as it plays a crucial role in determining the optimal recharging plan for our BEB fleets. It directly influences the accuracy of estimating the SOC of our BEBs, and any inaccuracies in specific consumption calculations can have far-reaching consequences for the overall efficiency and effectiveness of our recharging strategies. As we have previously explained, the operation of our buses is influenced by several stochastic factors, including road traffic flow states, traffic light states, queuing status at intersections, and passenger flows at stations. Consequently, the specific consumption of our BEBs is influenced by these factors, resulting in fluctuations and variations that can significantly impact our estimates of energy consumption and efficiency.

The specific consumption in the cost table that we have built in this Master's Thesis depends on time of day and SOC of BEB, as shown in Figure 4.6. To batter understand the dependence between specific consumption and time of day, and the dependence between specific consumption and SOC, we will analyse them separately in the following section.

As illustrated in Figure 4.7, the specific consumption of our BEBs exhibits notable differences even when performing the same bus route and with same initial SOC. This is attributed to the fact that the specific consumption is calculated based on the simulation of our BEBs, whose input is the driving cycle that we have constructed in the SUMO environment. As we have previously discussed, the driving cycle itself is subject to variations, not only in terms of trip duration but also in terms of the instant behavior of our BEBs, which is influenced by a complex

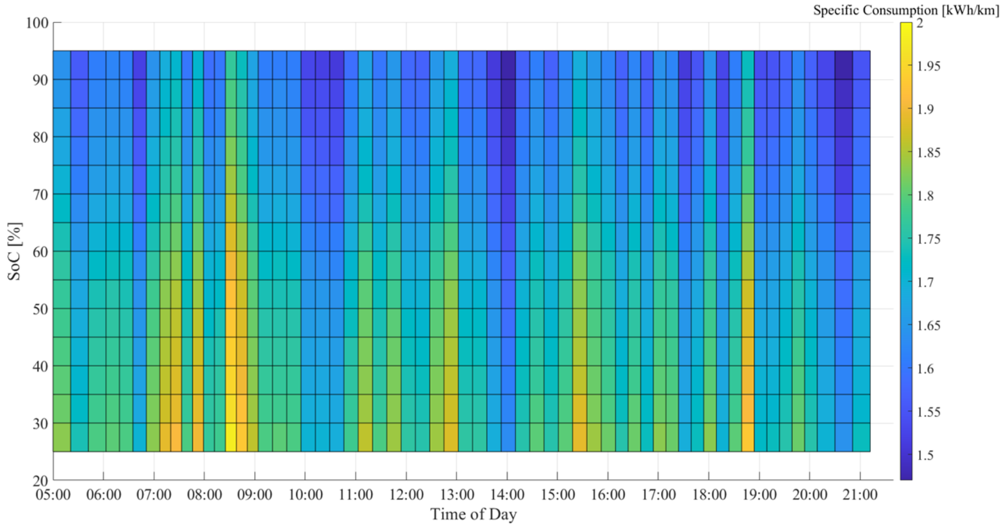


Figure 4.6: Specific Consumption Depends on Time of Day and SOC (Bus line 12 $North \rightarrow South$)

array of factors.

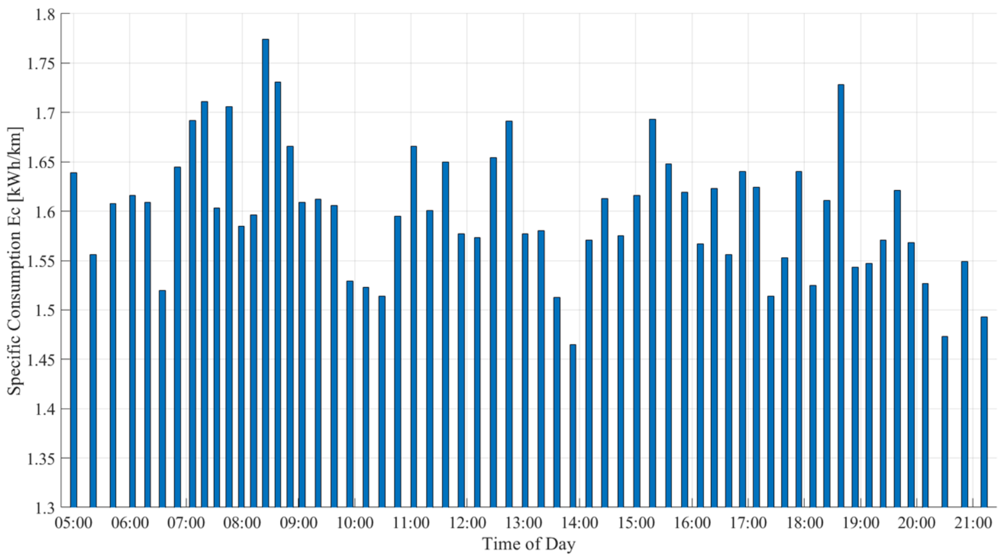


Figure 4.7: Specific Consumption of Bus Line 12 ($North \rightarrow South$)

However, in reality, the situation is even more complex, as the initial SOC of our BEBs is unlikely to be identical. To address this question, we have simulated various scenarios with different initial SOC values, and as shown in Figure 4.8, the specific consumption is observed to increase as the initial SOC of our BEBs decreases.

This finding emphasizes the importance of avoiding the use of fixed values for specific consumption, as this can lead to inaccurate estimates and suboptimal recharging strategies. In this project, we have taken a more precise approach, constructing cost tables that take into account the influence of SOC on specific consumption, thereby providing a more accurate and reliable framework for optimizing our BEB fleets recharging plans.

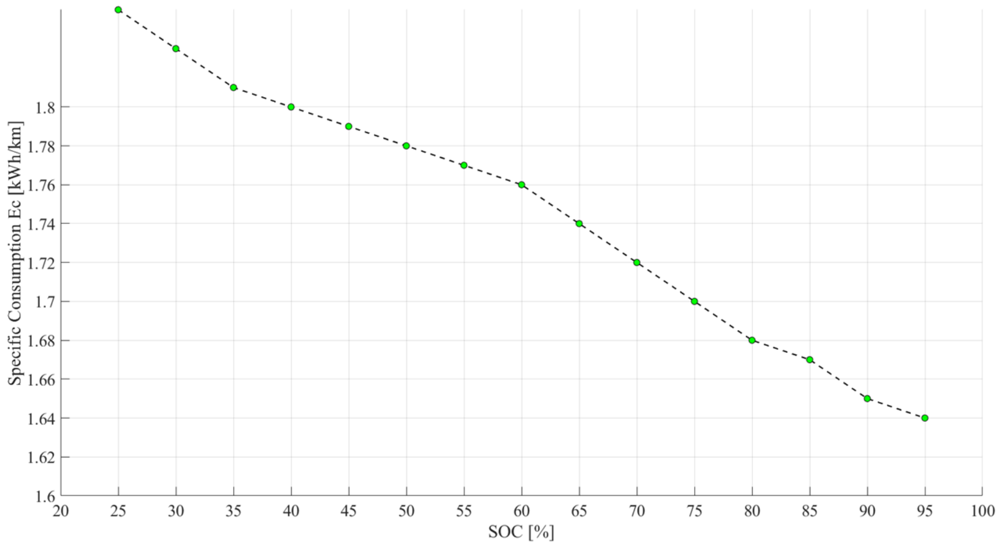


Figure 4.8: Specific Consumption Influenced by SOC of BEB

4.3 Optimal Charging Plan

Based on the cost tables and taking into consideration the additional constraints, the optimal charging plan for BEB fleet was obtained utilizing the algorithm described in Section 3.5. It is essential to highlight that our primary objective is to simultaneously minimize the number of BEBs in the fleet and the total cost of electricity charged to the BEBs for a single day. Moving forward, we will present the results we obtained and conduct an in-depth analysis of the influence exerted by TOU tariffs on our optimization model. Furthermore, we will also compare and contrast the distinct behavioral patterns exhibited by these two bus lines, thereby providing a comprehensive understanding of the optimal charging strategies for our BEB fleets.

4.3.1 Influence of TOU Tariffs

To conduct a thorough examination of the influence exerted by TOU tariffs, we present a comparison of the optimal charging plans for bus line 12 and bus line 58, as depicted in Figures 4.9 and 4.11, which incorporates the impact of TOU tariffs, and Figures 4.10 and 4.12, which neglects the influence of TOU tariffs, thereby providing a comprehensive analysis of the distinct effects of TOU tariffs on the charging patterns of our BEB fleet.

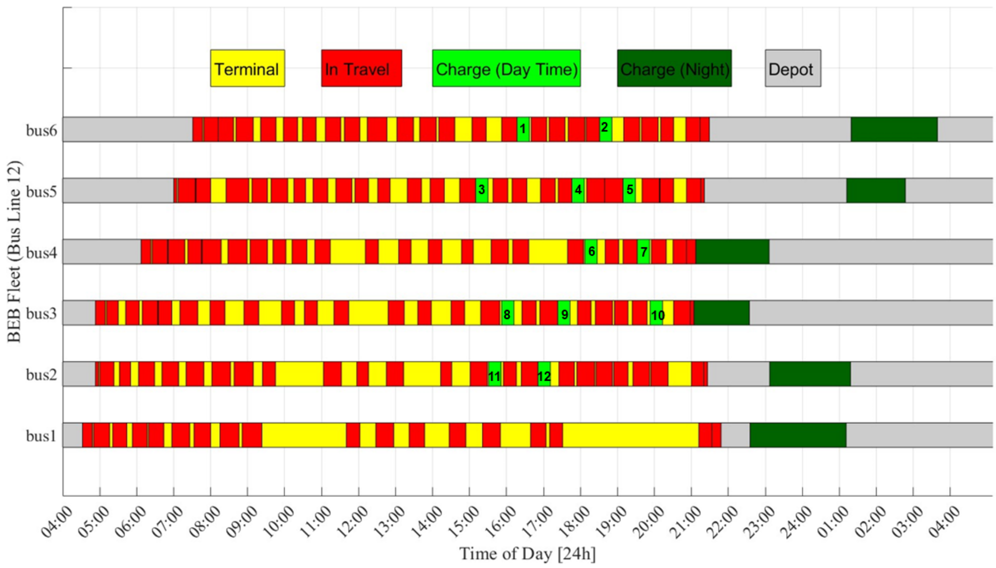


Figure 4.9: Optimal Charging Plan of Bus Line 12 (Consider TOU Tariffs)

In Figure 4.9 to 4.12, each row represents a specific BEB. The columns represent time, ranging from 4:00 AM to 4:00 AM the next day. The different colors represent

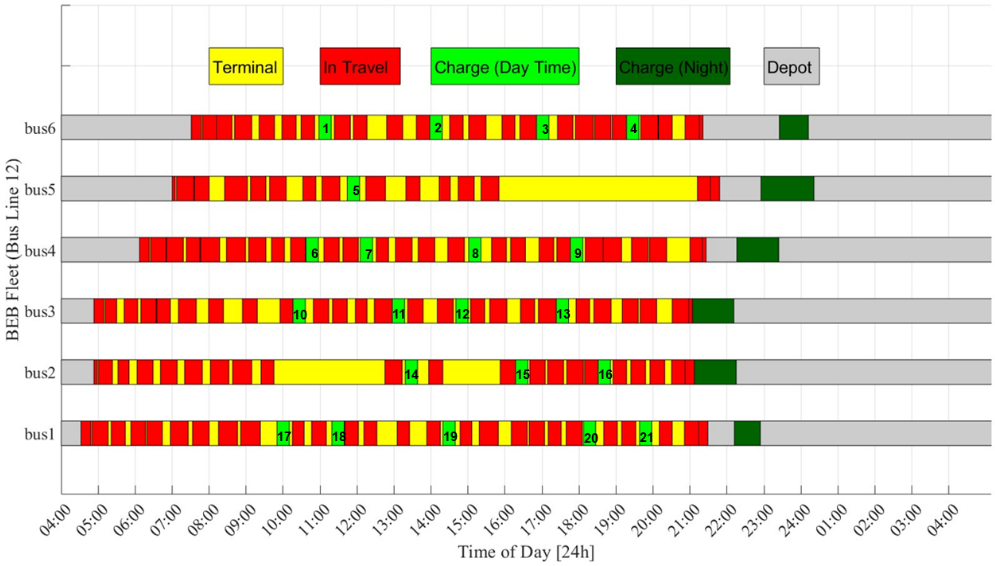


Figure 4.10: Optimal Charging Plan of Bus Line 12 (Not Consider TOU Tariffs)

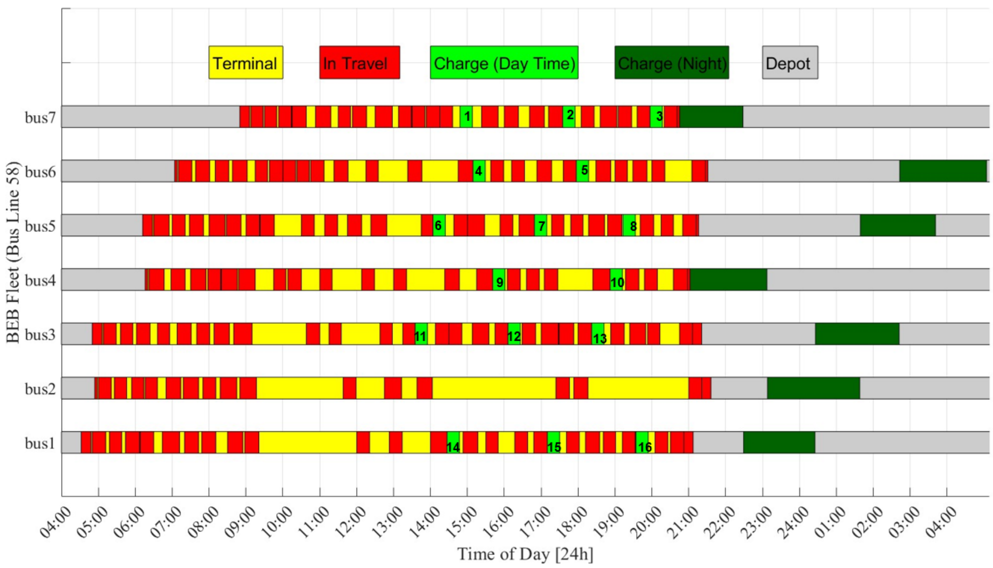


Figure 4.11: Optical Charging Plan of Bus Line 58 (Consider TOU Tariffs)

different states of the BEB's operation:

- Gray: At depot (Not in service and not in charging)
- Yellow: At the terminal (Not in service)
- Red: In travel (Service or Depot to Terminal or Terminal to Depot)

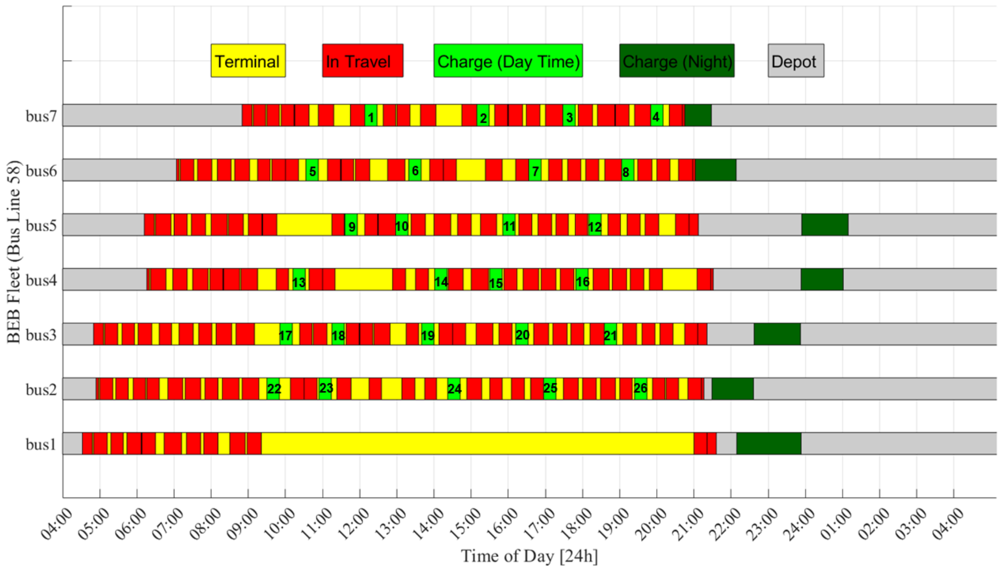


Figure 4.12: Optical Charging Plan of Bus Line 58 (Not Consider TOU Tariffs)

- Green: Charging (Day Time)
- Dark Green: Charging (Night Time)

For bus line 12, both in Figure 4.9 and Figure 4.10, the number of BEBs in the fleet remains consistently at 6. This constancy indicates that the total number of BEBs in the fleet is unaffected by the TOU tariffs. Despite any variations or changes in the TOU tariffs, the fleet size of 6 BEBs is maintained throughout the scenarios depicted in these figures.

A closer inspection of Figure 4.9 reveals that a total of 12 charging instances occur during the daytime period, whereas a striking contrast is observed in Figure 4.10, which exhibits a significantly higher frequency of 21 charging instances occurring during the same daytime period. This difference in charging patterns can be attributed to the consideration of TOU tariffs in the former figure.

In the absence of TOU tariff considerations, as shown in Figure 4.10, the BEBs can be charged during the daytime period if a terminal charging station is available and the BEB is in an idle state at the terminal. However, when TOU tariffs are taken into account, as shown in Figure 4.9, the charging activity is deferred to later periods, resulting in a longer charging duration during the nighttime period, as evident from the graphs. This contrast in charging patterns emphasise the pronounced influence of TOU tariffs on the optimal charging plans for our BEB fleets. The same story happens in bus line 58, which derives from Figure 4.11 and

Figure 4.12.

While the number of BEBs in the fleet for bus line 12 remains constant at 6, as depicted in Figures 4.9 and 4.10, and the number of BEBs in the fleet for bus line 58 remains constant at 7, showing in 4.11 and Figure 4.12, but the charging activities are quite different. Therefore it is crucial to explore how the SOC of each individual BEB varies throughout the day. The variation in SOC of bus line 12 and bus line 58 are presented in Figures 4.13 and 4.14 and Figures 4.15 and 4.16, separately.

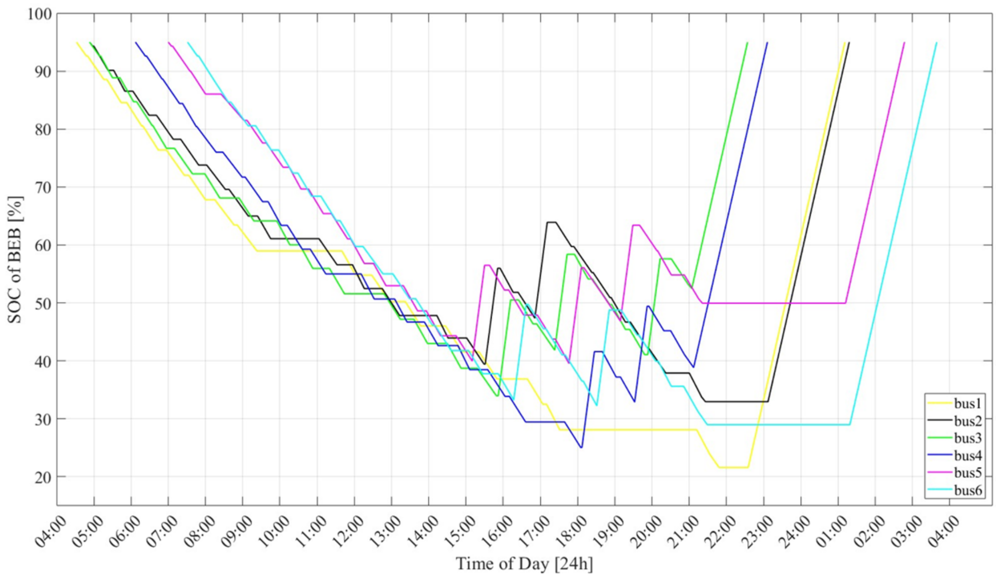


Figure 4.13: Variations of SOC of BEBs of Bus Line 12 (Consider TOU Tariffs)

These figures illustrate the SOC profiles of BEBs over a 24-hour period. The SOC, measured as a percentage, is plotted on the y-axis, which ranges from 20% to 100%. The x-axis represents the time of day, spanning from 4:00 AM to 4:00 AM the following day. This time frame captures a full daily cycle, providing a comprehensive view of the SOC dynamics.

It is evident that the SOC of the BEBs remains at a relatively low level in Figure 4.13 and 4.15 compared to Figure 4.14 and 4.16. Specifically, the minimum SOC value in Figure 4.13 and 4.15 hovers around 20%, whereas in Figure 4.14 and 4.16, the minimum SOC value is consistently above 50%. This significant difference in SOC levels between the two figures highlights the impact of TOU tariffs on the charging strategies of the BEBs.

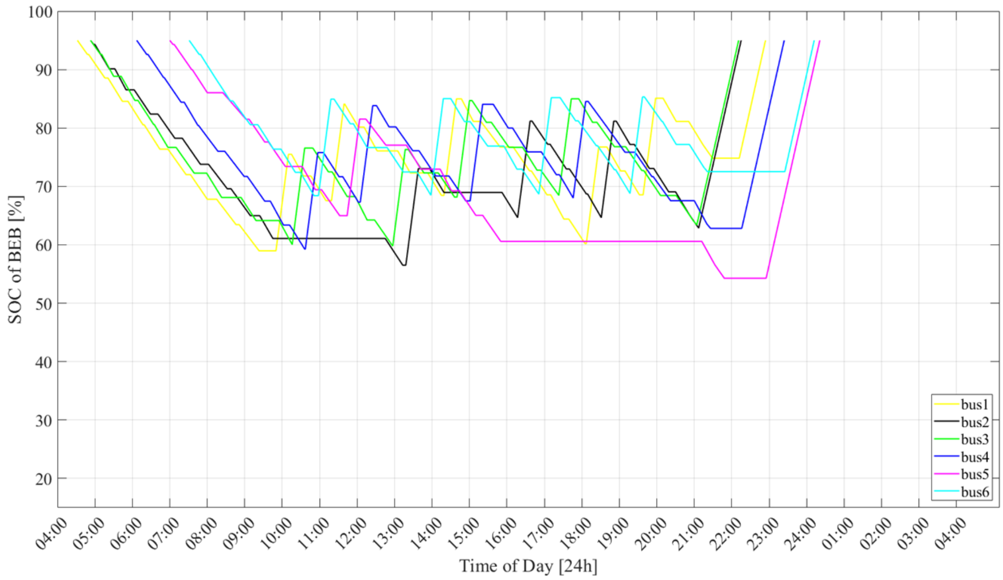


Figure 4.14: Variations of SOC of BEBs of Bus Line 12 (Not Consider TOU Tariffs)

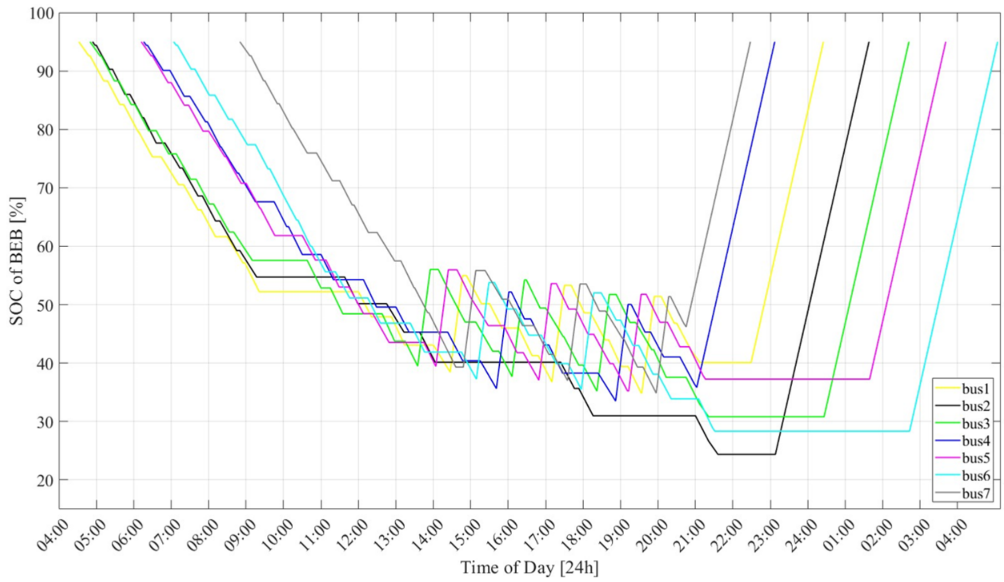


Figure 4.15: Variations of SOC of BEBs of Bus Line 58 (Consider TOU Tariffs)

In Figure 4.13 and 4.15, the lower SOC levels suggest that the BEBs are operating under a TOU tariff structure that possibly incentivizes charging during off-peak hours when electricity rates are lower. This can lead to more aggressive

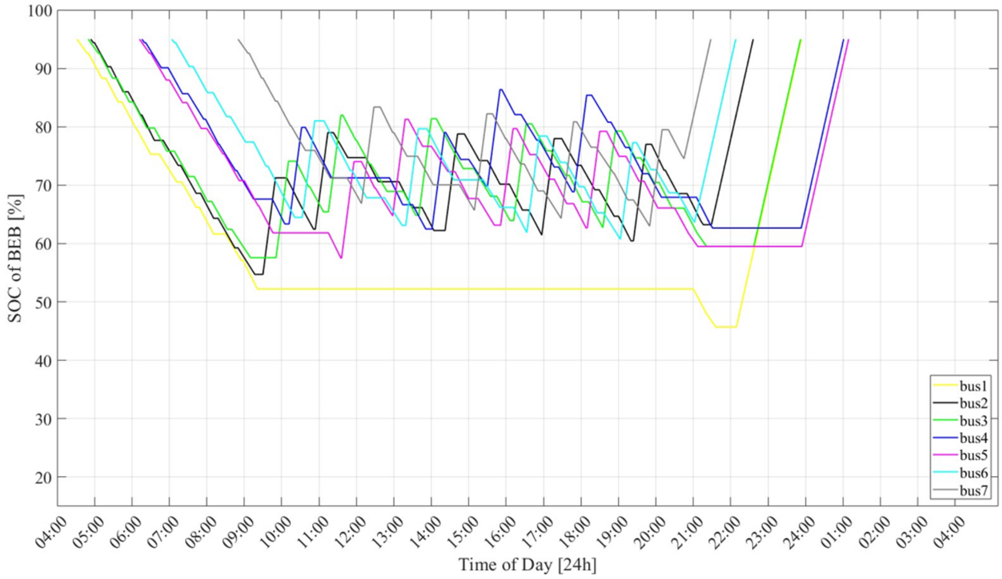


Figure 4.16: Variations of SOC of BEBs of Bus Line 58 (Not Consider TOU Tariffs)

discharge patterns during the day to maximize the utilization of cheaper electricity acquired during off-peak periods. As a result, BEBs might reach lower SOC levels before being recharged, reflecting a strategy aimed at reducing overall costs for charging the BEBs. The minimum SOC dropping to around 20% indicates that the fleet is pushing the limits of battery usage, ensuring that the energy stored during cheaper periods is maximally utilized.

On the other hand, Figure 4.14 and 4.16 show SOC levels that remain significantly higher, with the minimum SOC staying above 50%. The higher minimum SOC suggests that the BEBs are recharged more frequently. This strategy could also be reflective of a need to ensure that the BEBs always have sufficient charge to meet demands without risking a low battery.

The TOU tariffs directly influence these charging strategies by dictating the cost-effectiveness of charging at different times. The SOC differences illustrated in Figures 4.13 and 4.14 and Figures 4.15 and 4.16 highlight how TOU tariffs shape the charging and operational strategies of BEB fleets. Understanding these dynamics is crucial for optimizing energy costs, ensuring operational efficiency, and maintaining battery health over time. These insights can guide future decisions on tariff structures and charging policies to achieve a balance between cost savings and operational reliability.

4.3.2 Comparison of Results Between Different Bus Lines

In this project, we focus on optimizing the charging plan for two bus lines. The comparison of the input information and the resulting optimized charging plan is presented in Table 4.1. This table provides a overview of the key parameters used in the optimization process and the outcomes achieved through the implementation of the optimized charging strategy.

Bus Lines	**Bus Line 12**	**Bus Line 58**
INPUTS		
Numbers of Trips	123	147
Length of Trip	8.2 km	9.5 km (average)
Numbers of Charger (Terminal)	1 / Terminal	1 / Terminal
Power of Charger (Terminal)	160 kW	160 kW
Numbers of Charger (Depot)	2	2
Power of Charger (Depot)	90 kW	90 kW
RESULTS		
Numbers of BEBs	6	7
Numbers of charging (day time)	12 *times*	16 *times*

Table 4.1: Comparison Between Bus Line 12 and Bus Line 58

We can discern from the data presented in Table 4.1 that the number of BEBs allocated to bus line 58 is one more than that assigned to bus line 12. And a difference exists when we examine the frequency of charging activities between the two bus lines, with bus line 58 exhibiting 4 more charging instances than bus line 12. This notable difference can be attributed to two primary factors.

Firstly, bus line 58 operates 24 more trips than bus line 12, which contributes to the increased demand for BEBs and for charging. Secondly, the average trip length of bus line 58 is 1.3 kilometers longer than that of bus line 12, so it demands more energy, which further exacerbates the need for more frequent charging.

Upon closer inspection, we observe that the average number of trips per BEB is 20.5 for bus line 12, whereas bus line 58 averages 21 trips per BEB. This difference in trip frequencies translates to a higher utilization rate of BEBs on bus line 58, explaining the bus line's increased reliance on electric buses and, by extension, more frequent charging activities.

The detailed charging plan and variations in the SOC for the BEB fleet operating on bus line 58 are illustrated in Figure 4.11 and Figure 4.15. These figures provide a comprehensive view of how the charging strategy is implemented and its impact on the SOC levels of the BEBs over a 24-hour period.

Upon examining Figure 4.9, it becomes evident that the charging plan closely resembles that depicted in Figure 4.11. This similarity arises from the fact that both plans take into account the TOU tariffs, which significantly influence the scheduling of charging sessions. Due to the higher electricity prices during daytime hours, the charging plan strategically minimizes the number of charging sessions during these periods. This approach ensures that the bulk of the charging occurs during off-peak hours when electricity rates are lower, thereby reducing operational costs.

The SOC variations shown in Figure 4.13 align closely with those observed in Figure 4.15. In both figures, the SOC of the BEBs remains at a relatively lower level compared to the SOC levels in Figures 4.14 and 4.15. This lower SOC is a direct consequence of the optimized charging strategy aimed at minimizing charging costs.

4.4 Validation - Influence of Number of Passengers

The results we present in Section 4.3 are based on a constant number of passengers on the BEBs, as mentioned in Section 3.4. However, it is well understood that maintaining a fixed number of passengers on board throughout a day's operation is unrealistic [72]. The passenger count on BEBs fluctuates due to various factors such as time of day, route, and demand patterns.

To address this variability, we must consider the influence of changing passenger numbers. As discussed in Section 3.6, we will use various passenger numbers, shown in Figures 3.12 and 3.13. This approach allows us to model more realistic scenarios where passenger numbers vary, thereby impacting the energy consumption and charging requirements of the BEBs.

In light of this, we proceed to validate the SOC of battery for both bus line 12 and bus line 58. By doing so, we aim to assess the robustness and effectiveness of the charging strategy under varying passenger loads. This validation will help us understand how well the charging plan adapts to real-world conditions and ensure that the BEBs can maintain efficient operation without interruptions.

4.4.1 Validated SOC of Battery

In Section 3.6.1, we have presented the number of passengers on BEBs used for the validation process in this section. Under the optimal charging plan, the validated SOC of battery for bus line 12 and bus line 58 are illustrated in Figure 4.17 and Figure 4.18, represented by the dashed lines.

These figures reveal differences of the SOC in the validation results and in the optimization results. This discrepancy highlights the impact of the fluctuating number of passengers on BEBs on the energy consumption.

During the optimization process, a constant number of passengers was assumed, simplifying the model but potentially reducing its accuracy. However, the validation results, which incorporate variations in the number of passengers throughout the day, demonstrate a more realistic scenario. The SOC variations in the validation results are more dynamic and responsive to changes in passenger load, suggesting that the actual energy consumption of the BEBs differ from the optimized predictions.

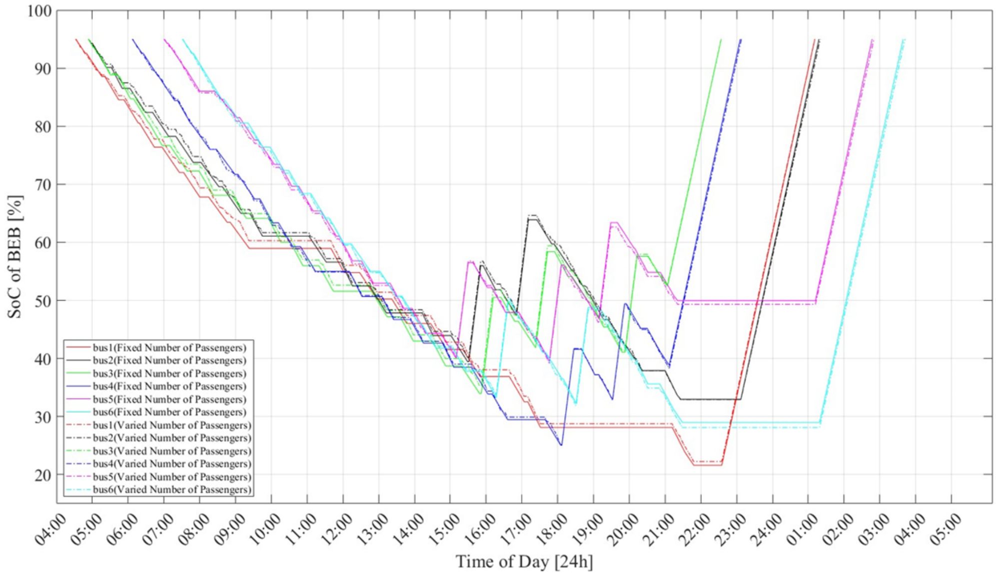


Figure 4.17: Validation for Bus Line 12

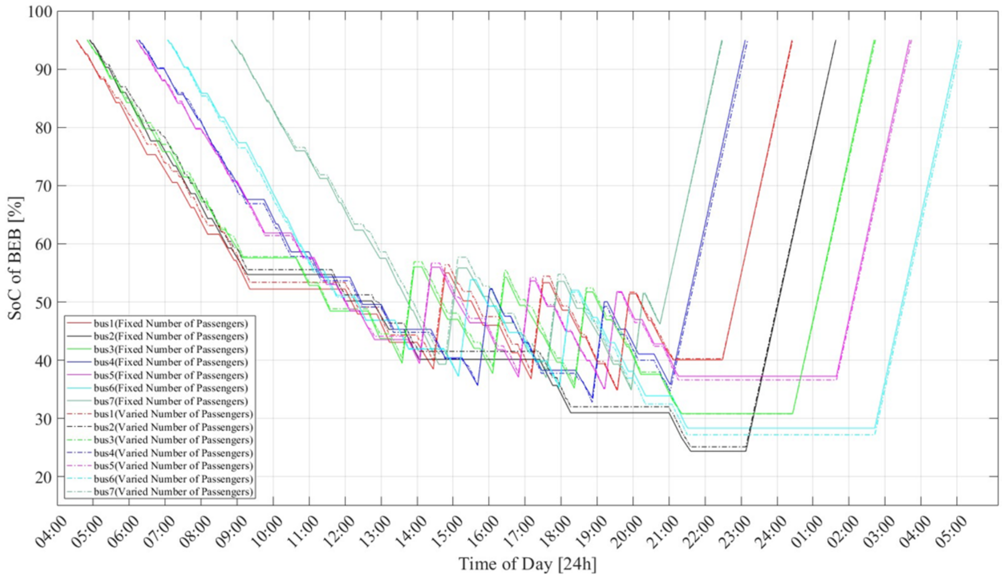


Figure 4.18: Validation for Bus Line 58

To gain deeper insights, Figures 4.19 and 4.20 illustrate the difference between validated SOC across various passengers and optimized SOC for fixed passengers. Specifically, for bus line 12, the maximum SOC difference is under 2%, whereas for bus line 58, it remains below 3%. These figures highlight the efficiency and reliability of the optimization process in maintaining SOC levels close to validated

SOC across different bus lines.

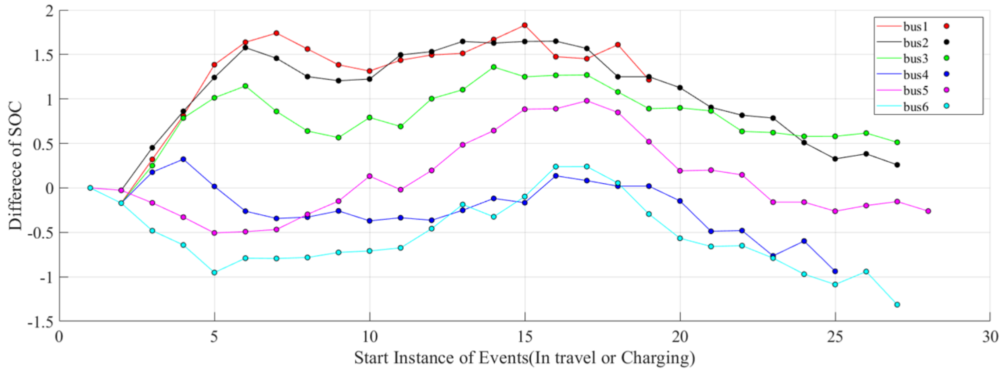


Figure 4.19: Difference Between Validated SOC and Optimization SOC (Bus Line 12)

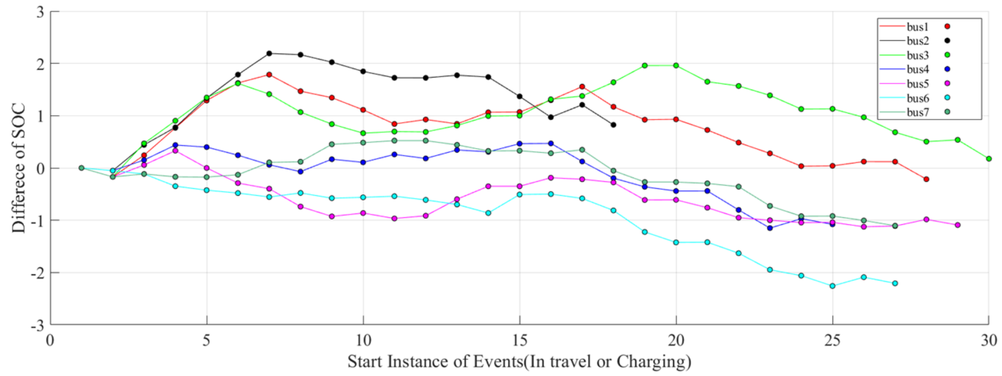


Figure 4.20: Difference Between Validated SOC and Optimization SOC (Bus Line 58)

Despite these differences, the optimization charging plan demonstrates that the overall strategy can still be effectively applied in a practical context. This feasibility is crucial because it shows that our approach can adapt to actual operating conditions, ensuring that BEBs maintain adequate SOC levels throughout their service periods.

To develop a more accurate and practical charging plan, it is essential to account for the variation in passenger numbers. Passenger load directly influences the energy consumption of BEBs, heavier loads leading to higher energy use. By incorporating these variations into the charging plan, we can better align the theoretical model with real-world conditions, leading to more reliable and efficient energy management for the BEBs.

Chapter 5

Conclusion

This Master's Thesis proposes a four-step vehicle simulation-based planning method for recharging BEB fleets. The method accounts for factors such as traffic conditions, driving cycle, SOC of the battery, TOU tariffs, and the number of passengers. The goal is to provide an optimal charging plan that minimizes both the number of BEBs required and the overall cost of electricity for charging the BEBs.

In the first step, a unique driving cycle for each bus line at every predefined scheduled time instance was constructed using MATLAB-SUMO co-simulation. These driving cycles capture the dynamic behavior of drivers and account for traffic flows and traffic lights. The driving cycles vary not only for different scheduled times on the same bus line but also across different bus lines.

In the second step, cost tables were created using a backward energy consumption model, with driving cycles as input. Our BEB model incorporates the efficiency of the EM and the recovery of braking energy, resulting in more accurate energy consumption estimates. The cost table illustrates the consistency of trip length, the stochasticity of trip duration, and the dependence of energy consumption on the time of day and the SOC of the battery.

In the third step, an optimization algorithm was developed which aimed at simultaneously minimizing both the number of BEBs and the overall cost of electricity for charging them. This algorithm provided the optimal charging plan, both with and without considering TOU tariffs. The decision to charge BEB by fast charger is significantly influenced by the TOU tariffs.

In the final step, the impact of passenger numbers on BEBs to energy consumption was validated, demonstrating a discernible influence. Despite this, under same charging plan, the maximum difference in SOC between validated and optimized values remains below 3% for both bus lines. Although differences exist between optimized and validated SOC figures, the optimal charging plan derived from our method proves practical for real-world implementation. This observation strengthens the rationale that our approach to developing BEB fleet charging strategies is both sensible and viable.

Appendix A

Detailed Bus Schedules

The detailed bus schedules are shown in Table A.1 - A.4.

Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time
1	5:00	17	9:04	33	13:36	49	17:54
2	5:21	18	9:21	34	13:53	50	18:09
3	5:42	19	9:38	35	14:10	51	18:24
4	6:03	20	9:55	36	14:27	52	18:39
5	6:19	21	10:12	37	14:44	53	18:54
6	6:35	22	10:29	38	15:01	54	19:09
7	6:51	23	10:46	39	15:18	55	19:24
8	7:07	24	11:03	40	15:35	56	19:39
9	7:20	25	11:20	41	15:52	57	19:54
10	7:33	26	11:37	42	16:09	58	20:09
11	7:46	27	11:54	43	16:24	59	20:30
12	7:59	28	12:11	44	16:39	60	20:51
13	8:12	29	12:28	45	16:54	61	21:12
14	8:25	30	12:45	46	17:09	-	-
15	8:35	31	13:02	47	17:24	-	-
16	8:51	32	13:19	48	17:39	-	-

Table A.1: Bus Schedule for "Line 12 Southward"

Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time
1	4:50	17	9:54	33	13:22	49	17:40
2	5:11	18	9:07	34	13:39	50	17:55
3	5:32	19	9:24	35	13:56	51	18:10
4	5:53	20	9:41	36	14:13	52	18:25
5	6:09	21	9:58	37	14:30	53	18:40
6	6:25	22	10:15	38	14:47	54	18:55
7	6:57	23	10:32	39	15:04	55	19:10
8	7:10	24	10:49	40	15:21	56	19:25
9	7:20	25	11:06	41	15:38	57	19:40
10	7:23	26	11:23	42	15:55	58	19:55
11	7:36	27	11:40	43	16:10	59	20:10
12	7:49	28	11:57	44	16:25	60	20:31
13	8:02	29	12:14	45	16:40	61	20:52
14	8:15	30	12:31	46	16:55	62	21:00
15	8:28	31	12:48	47	17:10	-	-
16	8:41	32	13:05	48	17:25	-	-

Table A.2: Bus Schedule for "Line 12 Northward"

Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time
1	5:00	20	8:50	39	13:30	58	17:48
2	5:18	21	9:00	40	13:45	59	18:00
3	5:36	22	9:15	41	14:00	60	18:12
4	5:54	23	9:30	42	14:15	61	18:24
5	6:08	24	9:45	43	14:30	62	18:36
6	6:22	25	10:00	44	14:45	63	18:48
7	6:36	26	10:15	45	15:00	64	19:00
8	6:50	27	10:30	46	15:15	65	19:12
9	7:00	28	10:45	47	15:30	66	19:24
10	7:10	29	11:00	48	15:45	67	19:36
11	7:20	30	11:15	49	16:00	68	19:48
12	7:30	31	11:30	50	16:12	69	20:00
13	7:40	32	11:45	51	16:24	70	20:15
14	7:50	33	12:00	52	16:36	71	20:30
15	8:00	34	12:15	53	16:48	72	20:45
16	8:10	35	12:30	54	17:00	73	21:00
17	8:20	36	12:45	55	17:12	-	-
18	8:30	37	13:00	56	17:24	-	-
19	8:40	38	13:15	57	17:36	-	-

Table A.3: Bus Schedule for "Line 58 Southward"

Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time	Trip ID	Trip Time
1	4:50	20	8:48	39	13:23	58	17:41
2	5:08	21	8:58	40	13:38	59	17:53
3	5:26	22	9:08	41	13:53	60	18:05
4	5:44	23	9:23	42	14:08	61	18:17
5	6:02	24	9:38	43	14:23	62	18:29
6	6:16	25	9:53	44	14:38	63	18:41
7	6:30	26	10:08	45	14:53	64	18:53
8	6:44	27	10:23	46	15:08	65	19:05
9	6:58	28	10:38	47	15:23	66	19:17
10	7:08	29	10:53	48	15:38	67	19:29
11	7:18	30	11:08	49	15:53	68	19:41
12	7:28	31	11:23	50	16:05	69	19:53
13	7:38	32	11:38	51	16:17	70	20:05
14	7:48	33	11:53	52	16:29	71	20:20
15	7:58	34	12:08	53	16:41	72	20:35
16	8:08	35	12:23	54	16:53	73	20:50
17	8:18	36	12:38	55	17:05	74	21:05
18	8:28	37	12:53	56	17:17	-	-
19	8:38	38	13:08	57	17:29	-	-

Table A.4: Bus Schedule for "Line 58 Northward"

Appendix B

Detailed Cost Table

One detailed cost table of bus line 12 $North \rightarrow South$ with initial SOC 95% is shown in Table B.1.

T_{start}	L_{trip} (km)	E_{con} (kWh)	Ec (kWh/km)	T_{dura} (min)	T_{end}
5:00	8.2	13.04	1.59	23	5:23
5:21	8.2	12.41	1.51	23	5:44
5:42	8.2	12.83	1.56	22	6:04
6:03	8.2	12.93	1.57	26	6:29
6:19	8.2	12.86	1.57	25	6:44
6:35	8.2	12.12	1.48	22	6:57
6:51	8.2	13.16	1.60	27	7:18
7:07	8.2	13.53	1.65	28	7:35
7:20	8.2	13.66	1.66	29	7:49
7:33	8.2	12.83	1.56	27	8:00
7:46	8.2	13.67	1.66	31	8:17
7:59	8.2	12.64	1.54	24	8:23
8:12	8.2	12.74	1.55	25	8:37
8:25	8.2	14.22	1.73	37	9:02
8:38	8.2	13.82	1.69	31	9:09
8:51	8.2	13.36	1.63	32	9:23
9:04	8.2	12.88	1.57	28	9:32
9:21	8.2	12.88	1.57	25	9:46
9:38	8.2	12.85	1.57	27	10:05
9:55	8.2	12.20	1.49	21	10:16
10:12	8.2	12.13	1.48	24	10:36

T_{start}	L_{trip} (km)	E_{con} (kWh)	Ec (kWh/km)	T_{dura} (min)	T_{end}
10:29	8.2	12.09	1.47	22	10:51
10:46	8.2	12.73	1.55	24	11:10
11:03	8.2	13.27	1.62	29	11:32
11:20	8.2	12.79	1.56	24	11:44
11:37	8.2	13.18	1.60	25	12:02
11:54	8.2	12.59	1.53	22	12:16
12:11	8.2	12.56	1.52	21	12:32
12:28	8.2	13.25	1.61	29	12:57
12:45	8.2	13.52	1.64	28	13:13
13:02	8.2	12.62	1.54	27	13:29
13:19	8.2	12.61	1.54	23	13:42
13:36	8.2	12.09	1.47	22	13:58
13:53	8.2	11.71	1.43	22	14:15
14:10	8.2	12.57	1.53	26	14:36
14:27	8.2	12.91	1.57	27	14:54
14:44	8.2	12.57	1.53	26	15:10
15:01	8.2	12.93	1.57	28	15:29
15:18	8.2	13.56	1.65	31	15:49
15:35	8.2	13.20	1.61	28	16:03
15:52	8.2	12.95	1.58	25	16:17
16:09	8.2	12.53	1.53	24	16:33
16:24	8.2	12.97	1.58	27	16:51
16:39	8.2	12.43	1.51	25	17:04
16:54	8.2	13.14	1.60	29	17:23
17:09	8.2	12.95	1.58	26	17:35
17:24	8.2	12.09	1.47	22	17:46
17:39	8.2	12.43	1.51	26	18:05
17:54	8.2	13.15	1.60	29	18:23
18:09	8.2	12.16	1.48	22	18:31
18:24	8.2	12.90	1.57	28	18:52
18:39	8.2	13.79	1.68	30	19:09
18:54	8.2	12.33	1.50	23	19:17
19:09	8.2	12.37	1.51	23	19:32
19:24	8.2	12.54	1.53	24	19:48
19:39	8.2	12.97	1.58	27	20:06
19:54	8.2	12.57	1.53	28	20:22
20:09	8.2	12.17	1.48	22	20:31
20:30	8.2	11.78	1.43	22	20:52

T_{start}	L_{trip} (km)	E_{con} (kWh)	Ec (kWh/km)	T_{dura} (min)	T_{end}
20:51	8.2	12.36	1.51	23	21:14
21:12	8.2	11.88	1.45	21	21:33

Table B.1: Cost Table of Bus Line 12 ($North \rightarrow South$) with Initial SOC of 95%

Bibliography

[1] X. Han and L. P. Naeher. «A review of traffic-related air pollution exposure assessment studies in the developing world». In: *Environment International* 32 (Jan. 2006), pp. 106–120 (cit. on p. 1).

[2] OECD / IEA / IIASA. *Energy and Air Pollution: World Energy Outlook Special Report 2016*. https://pure.iiasa.ac.at/id/eprint/13467: International Energy Agency, 2016 (cit. on p. 1).

[3] *WHO. Air Pollution.* `http://www.who.int/airpollution/en/`, visited on 2024-5-25 (cit. on p. 1).

[4] I. Manisalidis, E. Stavropoulou, A. Stavropoulos, and E. Bezirtzoglou. «Environmental and Health Impacts of Air Pollution: A Review». In: *Front. Public Health* 8 (Feb. 2020) (cit. on p. 1).

[5] I. Stoddard and K. Anderson. «Three Decades of Climate Mitigation: Why Haven't We Bent the Global Emissions Curve?» In: *ANNUAL REVIEW OF ENVIRONMENT AND RESOURCES* 46 (June 2021), pp. 653–689 (cit. on p. 2).

[6] P. Achakulwisut, P. Erickson, C. Guivarch, R. Schaeffer, E. Brutschin, and S. Pye. «Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions». In: *Nature Communications* 14 (Sept. 2023), p. 5452 (cit. on p. 2).

[7] *ITF, OECD. (May 24, 2023). Global urban passenger travel demand for bus travel from 2019 to 2022 with a forecast through 2050, by region (in billion passenger kilometers) [Graph]. In Statista.* `https://www.statista.com/statistics/1402477/worldwide-urban-passenger-travel-demand-for-travel-by-bus/`, visited on 2024-06-24 (cit. on p. 2).

[8] O.J. Ibarra-Rojas, F. Delgado, R. Giesen, and J.C. Muñoz. «Planning, operation, and control of bus transport systems: A literature review». In: *Transportation Research Part B: Methodological* 77 (July 2017), pp. 38–75 (cit. on p. 2).

[9] *acea, DRIVING MOBILITY FOR EUROPE.* `https://www.acea.auto/fuel-cv/fuel-types-of-new-buses-electric-12-7-diesel-67-3-market-share-full-year-2022/`, visited on 2024-06-24 (cit. on pp. 2, 3).

[10] T. Orhan and İ. Nakir. «Total Cost of Ownership Based Economic Analysis of Diesel, CNG and Electric Bus Concepts for the Public Transport in Istanbul City». In: *Energies* 11 (Sept. 2018), p. 2369 (cit. on pp. 2, 3).

[11] M. Mahmoud, R. Garnett, M. Ferguson, and P. Kanaroglou. «Electric buses: A review of alternative powertrains». In: *Renewable and Sustainable Energy Reviews* 62 (Sept. 2016), pp. 673–684 (cit. on pp. 2–4).

[12] B. Zhou, Y. Wu, B. Zhou, R. Wang, W. Ke, S. Zhang, and J. Hao. «Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions». In: *Energy* 96 (Feb. 2016), pp. 603–613 (cit. on p. 2).

[13] A. Lajunen. «Energy consumption and cost-benefit analysis of hybrid and electric city buses». In: *Transportation Research Part C: Emerging Technologiest* 38 (Jan. 2014), pp. 1–15 (cit. on p. 3).

[14] R. Kühne. «Electric buses – An energy efficient urban transportation means». In: *Energy* 35 (Dec. 2015), pp. 4510–4513 (cit. on p. 3).

[15] R. Günther, T. Wenzel, M. Wegner, and R. Rettig. «Big data driven dynamic driving cycle development for busses in urban public transportation». In: *Transportation Research Part D: Transport and Environment* 51 (Mar. 2017), pp. 276–289 (cit. on p. 3).

[16] D. C.S. Beddows and R. M. Harrison. «PM10 and PM2.5 emission factors for non-exhaust particles from road vehicles: Dependence upon vehicle mass and implications for battery electric vehicles». In: *Atmospheric Environment* 244 (Jan. 2021), p. 117886 (cit. on p. 3).

[17] D. Tarvydas, I. Tsiropoulos, and N.Lebedeva. *Li-ion batteries for mobility and stationary storage applications – Scenarios for costs and market growth.* https://data.europa.eu/doi/10.2760/87175: European Commission, Joint Research Centre, Publications Office, 2018 (cit. on p. 3).

[18] S. Soylu. «Development of PN emission factors for the real world urban driving conditions of a hybrid city bus». In: *Applied Energy* 138 (Jan. 2015), pp. 488–495 (cit. on p. 3).

[19] J. Miles and S. Potter. «Developing a viable electric bus service: The Milton Keynes demonstration project». In: *Research in Transportation Economics* 48 (Dec. 2014), pp. 357–363 (cit. on p. 4).

[20] H. Tu, H. Feng, S. Srdic, and S. Lukic. «Extreme Fast Charging of Electric Vehicles: A Technology Overviewt». In: *IEEE Transactions on Transportation Electrification* 5 (Dec. 2019), pp. 861–878 (cit. on p. 4).

[21] A. Tomaszewska, Z. Chu, X. Feng, S. O'Kane, and X. Liu. «Lithium-ion battery fast charging: A review». In: *eTransportation* 1 (Aug. 2019) (cit. on p. 4).

[22] M. Abdel-Monem, K. Trad, N. Omar, O. Hegazy, P. V. Bossche, and J. V. Mierlo. «Influence analysis of static and dynamic fast-charging current profiles on ageing performance of commercial lithium-ion batteries». In: *Energy* 120 (Feb. 2017), pp. 179–191 (cit. on p. 4).

[23] M. Gilleran, E. Bonnema, J. Woods, P. Mishra, I. Doebber, C. Hunter, M. Mitchell, and M. Mann. «Impact of electric vehicle charging on the power demand of retail buildings». In: *Advances in Applied Energy* 4 (Nov. 2021) (cit. on p. 4).

[24] S. Borozan, S. Giannelos, and G. Strbac. «Strategic network expansion planning with electric vehicle smart charging concepts as investment options». In: *Advances in Applied Energy* 5 (Feb. 2022) (cit. on p. 4).

[25] Y. Wang, Y. Huang, J. Xu, and N. Barclay. «Optimal recharging scheduling for urban electric buses: A case study in Davis». In: *Transportation Research Part E: Logistics and Transportation Review* 100 (Apr. 2017), pp. 115–132 (cit. on pp. 4, 6, 8, 37).

[26] Y. He, Z. Liu, and Z. Song. «Optimal charging scheduling and management for a fast-charging battery electric bus system». In: *Transportation Research Part E: Logistics and Transportation Review* 142 (Oct. 2020) (cit. on pp. 4, 7, 37).

[27] Z. Bao, J. Li, X. Bai, C. Xie, Z. Chen, M. Xu, W. Shang, and H. Li. «An optimal charging scheduling model and algorithm for electric buses». In: *Applied Energy* 332 (Feb. 2023) (cit. on pp. 4, 7, 37, 38).

[28] B. Ke, C. Chung, and Y. Chen. «Minimizing the costs of constructing an all plug-in electric bus transportation system: A case study in Penghu». In: *Applied Energy* 177 (Sept. 2016), pp. 649–660 (cit. on p. 8).

[29] T. Paul and H. Yamada. «Operation and charging scheduling of electric buses in a city bus route network». In: (Oct. 2014), pp. 2780–2786 (cit. on p. 8).

[30] M. Xylia, S. Leduc, P. Patrizio, F. Kraxner, and S. Silveira. «Locating charging infrastructure for electric buses in Stockholm». In: *Transportation Research Part C: Emerging Technologies* 78 (May 2017), pp. 183–200 (cit. on p. 8).

[31] N.-O. Nylund, K. Erkkilä, N. Clark, and G. Rideout. *Evaluation of duty cycles for heavy-duty urban vehicles: Final report of IEA AMF Annex XXIX*. https://publications.vtt.fi/pdf/tiedotteet/2007/T2396.pdf: VTT Technical Research Centre of Finland, 2007 (cit. on pp. 8, 9).

[32] O. Vilppo and J. Markkula. «Feasibility of Electric Buses in Public Transport». In: *World Electric Vehicle Journal* 7 (Sept. 2015), pp. 357–365 (cit. on p. 8).

[33] A. Lajunen and T. Lipman. «Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses». In: *Energy* 106 (July 2016), pp. 329–342 (cit. on p. 8).

[34] G.D. Filippo, V. Marano, and R. Sioshansi. «Simulation of an electric transportation system at The Ohio State University». In: *Applied Energy* 113 (Jan. 2014), pp. 1686–1691 (cit. on p. 8).

[35] P. Shen, Z. Zhao, J. Li, and X. Zhan. «Development of a typical driving cycle for an intra-city hybrid electric bus with a fixed route». In: *Transportation Research Part D: Transport and Environment* 59 (Mar. 2018), pp. 346–360 (cit. on p. 9).

[36] P. Sinhuber, W. Rohlfs, and D. U. Sauer. «Study on power and energy demand for sizing the energy storage systems for electrified local public transport buses». In: (Oct. 2012), pp. 315–320 (cit. on p. 9).

[37] M. Rogge, S. Wollny, and D.U. Sauer. «Fast Charging Battery Buses for the Electrification of Urban Public Transport—A Feasibility Study Focusing on Charging Infrastructure and Energy Storage Requirements». In: *Energies* 8 (May 2015), pp. 4587–4606 (cit. on p. 9).

[38] T. Ly, D. Goehlich, and L. Heide. «Assessment of the Interaction of Charging System and Battery Technology for the Use in Urban Battery Electric Bus Systems». In: (Oct. 2016), pp. 1–6 (cit. on p. 9).

[39] B. Zhou, Y. Wu, B. Zhou, R. Wang, W. Ke, S. Zhang, and J. Hao. «Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions». In: *Energy* 96 (Feb. 2016), pp. 603–613 (cit. on p. 9).

[40] Z. Gao, Z. Lin, T.J. LaClair, C. Liu, J. Li, A.K. Birky, and J. Ward. «Battery capacity and recharging needs for electric buses in city transit service». In: *Energy* 122 (Mar. 2017), pp. 588–600 (cit. on p. 9).

[41] P. Pettersson, B. Jacobson, F. Bruzelius, P. Johannesson, and L. Fast. «Intrinsic differences between backward and forward vehicle simulation models». In: *IFAC-PapersOnLine* 53 (July 2020), pp. 14292–14299 (cit. on pp. 10, 11).

[42] F. L. Mapelli and D. Tarsitano. «Modeling of Full Electric and Hybrid Electric Vehicles». In: *New Generation of Electric Vehicles, London, UK: IntechOpen* (2012), pp. 207–236 (cit. on p. 10).

[43] J. Vepsäläinen, K. Kivekäs, K. Otto, A. Lajunen, and K. Tammi. «Development and validation of energy demand uncertainty model for electric city buses». In: *Transportation Research Part D: Transport and Environment* 63 (Aug. 2018), pp. 347–361 (cit. on p. 11).

[44] R. Manca, E. Tramacere, S. Favelli, A. Tonoli, and L. Camosi. «Impact of Rolling Resistance Modeling on Energy Consumption for a Low Voltage Battery Electric Vehicle». In: *2023 International Symposium on Electromobility (ISEM)*. Monterrey, Mexico, Oct. 2023, pp. 1–6 (cit. on p. 11).

[45] S. Hegde, A. Bonfitto, H. Rahmeh, N. Amati, and A. Tonoli. «Optimal Selection of Equivalence Factors for ECMS in Mild Hybrid Electric Vehicles». In: *Proceedings of the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 1: 23rd International Conference on Advanced Vehicle Technologies (AVT)*. Virtual, Online, Aug. 2021 (cit. on p. 11).

[46] Joeri Van Mierlo, Peter Van Den Bossche, and Gaston Maggetto. «Simulation Methodologies For Innovative Vehicle Drive Systems». In: *11th International Conference EPE-PEMC'2004, Power Electronics and Motion control*. Riga, Latvia, Sept. 2004 (cit. on p. 11).

[47] U. Usmanov, S. Ruzimov, A. Tonoli, and A. Mukhitdinov. «Modeling, Simulation and Control Strategy Optimization of Fuel Cell Hybrid Electric Vehicle». In: *Vehicles* 5 (Apr. 2023), pp. 464–481 (cit. on p. 11).

[48] C. Fiori, K. Ahn, and H.A. Rakha. «Power-based electric vehicle energy consumption model: Model development and validation». In: *Applied Energy* 168 (Apr. 2016), pp. 257–268 (cit. on p. 12).

[49] Z. Gao, Z. Lin, T. J. LaClair, C. Liu, J.-M. Li, A. K. Birky, and J. Ward. «Battery capacity and recharging needs for electric buses in city transit service». In: *Energy* 122 (Mar. 2017), pp. 588–600 (cit. on pp. 16, 19).

[50] J.Y. Wong. *Theory of Ground Vehicles*. Third. Wiley-Interscience, 2001 (cit. on p. 17).

[51] K. N. Genikomsakis and G. Mitrentsis. «A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications». In: *Transportation Research Part D: Transport and Environment* 50 (Jan. 2017), pp. 98–118 (cit. on p. 19).

[52] J. Larminie and J. Lowry. *Electric Vehicle Technology Explained.* http://formulahybrid.ru/Books/new/Electric_Vehicle_Technology_Explained.pdf, John Wiley Sons, 2012 (cit. on p. 20).

[53] A. Ponso, A. Bonfitto, and G. Belingardi. «Route Planning for Electric Vehicles Including Driving Style, HVAC, Payload and Battery Health». In: *Energies* 16 (Jan. 2023), p. 4627 (cit. on pp. 22, 23).

[54] *MATLAB - Math. Graphics. Programming.* https://ch.mathworks.com/products/matlab.html, visited on 2023-10-25 (cit. on p. 23).

[55] *Eclipse SUMO - Simulation of Urban MObility.* https://eclipse.dev/sumo/, visited on 2023-10-25 (cit. on pp. 23, 25, 28).

[56] *TraCI4Matlab. June 11, 2023.* https://www.mathworks.com/matlabcentral/fileexchange/44805-traci4matlab, visited on 2023-10-25 (cit. on p. 23).

[57] *OpenStreetMap.* https://www.openstreetmap.org/, visited on 2023-11-1 (cit. on p. 25).

[58] *GTT.* https://www.gtt.to.it/cms/percorari/urbano, visited on 2023-11-1 (cit. on pp. 25, 27).

[59] T. Perger and H. Auer. «Energy efficient route planning for electric vehicles with special consideration of the topography and battery lifetime». In: *Energy Efficiency* 13 (Sept. 2020), pp. 1705–1726 (cit. on p. 27).

[60] A. T. Thorgeirsson, S. Scheubner, S. Fünfgeld, and F. Gauterin. «An Investigation Into Key Influence Factors for the Everyday Usability of Electric Vehicles». In: *IEEE Open Journal of Vehicular Technology* 1 (Oct. 2020), pp. 348–361 (cit. on p. 27).

[61] Adolf Darlington May. *Traffic flow fundamentals.* 1990 (cit. on p. 28).

[62] G. F. Newell. «Nonlinear Effects in the Dynamics of Car Following». In: *Operations Research* 9 (Apr. 1961), pp. 209–229 (cit. on p. 29).

[63] Y. He, Z. Liu, and Z. Song. «Optimal charging scheduling and management for a fast-charging battery electric bus system». In: *Transportation Research Part E: Logistics and Transportation Review* 142 (Oct. 2020), p. 102056 (cit. on p. 36).

[64] P. You, Z. Yang, Y. Zhang, S. H. Low, and Y. Sun. «Optimal Charging Schedule for a Battery Switching Station Serving Electric Buses». In: *IEEE Transactions on Power Systems* 31 (Sept. 2016), pp. 3473–3483 (cit. on p. 36).

[65] A. Bagherinezhad, A. D. Palomino, B. Li, and M. Parvania. «Spatio-Temporal Electric Bus Charging Optimization With Transit Network Constraints». In: *IEEE Transactions on Industry Applications* 56 (Sept. 2020), pp. 5741–5749 (cit. on p. 36).

[66] M.E. van Kooten Niekerk, J.M. van den Akker, and J.A Hoogeveen. «Scheduling electric vehicles». In: *Public Transport* 9 (June 2017), pp. 155–176 (cit. on p. 36).

[67] B. Borlaug, M. Muratori, and M. Gilleran. «Heavy-duty truck electrification and the impacts of depot charging on electricity distribution systems». In: *Nature Energy* 6 (May 2021), pp. 673–682 (cit. on pp. 36, 38).

[68] N. Wassiliadis, J. Schneider, A. Frank, L. Wildfeuer, X. Lin, A. Jossen, and M. Lienkamp. «Review of fast charging strategies for lithium-ion battery systems and their applicability for battery electric vehicles». In: *Journal of Energy Storage* 44 (Dec. 2021), p. 103306 (cit. on p. 37).

[69] *GME Website*. (`https://www.mercatoelettrico.org/it/Esiti/MGP/EsitiMGP.aspx`, visited on 2023-11-1 (cit. on p. 38).

[70] Y. Bai, Z. Sun, B. Zeng, J. Deng, and C. Lip. «A multi-pattern deep fusion model for short-term bus passenger flow forecasting». In: *Applied Soft Computing* 58 (Sept. 2017), pp. 669–680 (cit. on p. 42).

[71] J. Zhang, D. Shen, L. Tu, F. Zhang, C. Xu, and et al. «A Real-Time Passenger Flow Estimation and Prediction Method for Urban Bus Transit Systems». In: *IEEE Transactions on Intelligent Transportation Systems* 18 (Nov. 2017), pp. 3168–3178 (cit. on p. 42).

[72] T. Liu, D. Guan, F. Gao, and Y. Wei. «Analysis on Characteristics of Bus Passenger Flow in Big Data Environment». In: *Proceedings of the 5th International Conference on Big Data Technologies (ICBDT '22)* (Sept. 2022), pp. 8–13 (cit. on pp. 42, 64).