An integrated approach to implementing opportunity charging for electric buses

A case study of Rotterdam

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by

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Preface

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Executive summary

This thesis demonstrates the necessity of an integrated approach that includes both mobility and energy systems for implementing effective electric bus (EB) charging strategies using opportunity charging.

The introduction of electric bus fleets (EBFs) creates a link between two critical systems—mobility and energy. Both systems are highly congested within urban areas and will continue to do so with the ever-increasing population. Therefore, synergy between mobility and energy systems is required to improve the livability of (future) urban areas.

Currently, the primary charging strategy for EBs involves overnight charging at depots. However, this alone is insufficient for daily operations, necessitating additional daytime charging. There are three main methods for daytime charging: depot charging, which leads to numerous non-revenue generating trips; terminal station charging, where buses have extended stop times at the endpoints of bus lines, such as train or metro stations; and intermediate stop charging during passenger boarding and alighting.

This research is particularly interested in the last method, known as opportunity charging. High-powered opportunity chargers, positioned at strategic points, could potentially meet daily operational needs with minimal interruption. Opportunity charging typically involves brief, high-intensity charging sessions in residential areas. A gap in the literature is identified here, as many studies overlook the impact of such charging strategies on the local electricity distribution grid. Existing research focusing on the grid impact of EB charging often considers multiple chargers at central locations, but not the scenario of a single charger in a residential area as explored in this thesis.

Furthermore, reducing the charging requirements and overall travel time benefits mobility and energy systems. Implementing traffic priority measures could benefit both charging requirements and travel time. However, research on how traffic prioritization for EBs influences their charging needs and the subsequent impact on the local distribution grid, especially regarding opportunity charging, is limited.

To bridge this gap, this thesis aims to answer the research question: **To what extent is the implementation of on-route opportunity charging possible when considering the mobility and energy systems simultaneously?**

This study employs two simulation tools to integrate mobility and energy considerations into the decision-making process. For mobility, SUMO—an open-source traffic simulation software—is used. SUMO provides this research with data regarding the energy requirements and charging times of the EB and provides insights into the necessary charging capacities and durations. For the energy system, this research makes use of Gaia. Gaia is a simulation software which provides this research with data regarding the impact of opportunity chargers on local grid congestion and, thus, whether charger capacities can be realised. The data of Gaia is based on real-life data and uses GO-E archetypes to make generalised assumptions about more than one grid. GO-E archetypes are a research tool developed by a consortium of companies and research institutes where grid data which has been stripped from personal information is available for research. Every postal code in the Netherlands is assigned to one of 8 archetypes. Conclusions about the protected grid data can, in some cases, provide insights into the operations of all postal codes assigned to that archetype.

The practical application of SUMO and Gaia in this research is demonstrated through a case study of a specific bus line: bus line 36 in Rotterdam. This case study helps to explore the practical aspects of integrating mobility and energy systems.

The case study is used to test five strategies to connect mobility and energy systems and investigate each system's influences on the operation of the other. The strategies are formulated as follows:

1. The first strategy does not interfere with the normal dwelling time of 20 seconds at the chargers. The charging capacity is 200 kW, corresponding to a mid-range fast charger.

2. The second strategy does not interfere with the normal dwelling time of 20 seconds, but to try and meet energy demands a charger of 450 kW is used. This strategy will highlight the difference in impact that a 450 kW charger has compared to a 200 kW charger on the distribution grid.

3. The third strategy changes the dwelling time at chargers to satisfy the energy requirements. The dwelling time will be increased until operation can be guaranteed with a 200 kW charger as a 450 kW charger caused, in most cases, too much grid congestion.

4. The fourth strategy introduces traffic priority. Traffic priority will influence the total energy requirements of the bus, as the bus will accelerate and decelerate less frequently. Additionally, a decrease in total travel time is found. The fourth strategy does not change the dwelling time found in strategy 3.

5. The fifth strategy uses traffic priority to decrease the dwelling time according to energy requirements. The last strategy will reduce the interference with the normal scheduling as much as possible.

The simulations of the different strategies in SUMO and Gaia are evaluated using the mobility and energy systems' requirements. Both systems are incredibly complex and have many factors influencing decision-making. However, the operators' goals of both systems can be simplified to basic requirements.

For the mobility system, the public transport operator (PTO) wants to satisfy demand as best as possible. For this research, it is assumed that the current timetable and route design satisfies demand. Therefore, the current design should be influenced as little as possible by the opportunity charging. This can be summarised in two requirements: the battery and its charge must be able to complete the current design (total number of trips per day) and charging should not influence the timetable to a great extent.

For the energy system, the power grid operator (PGO) wants to provide energy in a safe and consistent manner. This means the installed infrastructure should not degrade abnormally fast and safety should be guaranteed. To achieve a safe and consistent grid, the transformer should not exceed 100% regularly. Specific values for the requirements are listed for the case study area.

The mobility requirements are as follows:

1. The bus operation should be met by the battery level of the bus. In the case study, this means that the bus can not lose more than 8640 Watts for each round trip.

2. The timetable should preferably be changed as little as possible. In the case study, a maximum deviation of 10% is accepted.

   The energy requirement is as follows:

3. The transformer should not exceed 100% load rate regularly or continuously for extended periods.

The satisfaction of the requirement by the different strategies is shown in Table 1.

Strategy	**1**	**2**	**3**	**4**	**5**
Charger capacity	200 kW	450 kW	200 kW	200 kW	200 kW
Dwelling time	20 sec	20 sec	130 sec	130 sec	90 sec
Traffic priority	No	No	No	Yes	Yes
Requirement	**Satisfied?**				
The battery charge should not lose more than 8640 W	No	No	Yes	Yes	Yes
The timetable should not substantially be interfered with, with a maximum increase of 10%	Yes	Yes	No	No	Yes
The transformer should not exceed 100% regularly or continuously	Yes	No	Yes	Yes	Yes

Table 1: The satisfaction of the requirements of the mobility and energy systems by all strategies

The results presented in this thesis suggest that an EB route design with opportunity charging is impossible without considering both mobility and energy systems simultaneously. From the mobility perspective, opportunity charging is feasible only if the charging infrastructure can meet the buses' energy needs without disrupting the schedule. From the energy perspective, it is essential that opportunity charging is implemented where and when sufficient charging capacity is available.

Without traffic priority, it is impossible to satisfy all requirements. Either the charging capacities would be too high for the energy grid or the charging times would be too long for the EB service. Introducing traffic priority allows for the introduction of opportunity charging while satisfying all requirements by reducing the travel time (9,8%), thus increasing potential charging time, and reducing energy consumption (4,5%), thus decreasing charging requirements.

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Nomenclature

EB(s)	Electric bus(es)
EBF	Electric bus fleet
EV	Electric vehicle
GO-E	Gebouwde omgeving elektrificatie
LTC	Load tap changers
PEV	Personal electric vehicle
PGO	Power grid operator
PT	Public transport
PTO	Public transport operator
PV	Photovoltaic
SUMO	Simulation of Urban MObility
TRS	Traffic regulation system
TSS	Traffic simulation software
V2G	Vehicle to grid

1 Introduction

In 2015, 196 members of the United Nations adopted the Paris Agreement: A worldwide effort to reduce the emissions of greenhouse gasses to contain climate change within catastrophic bounds (United Nations, 2015). Road transportation accounts for 15% of total global CO_2 emissions (Nejat et al., 2015). Introducing Electric Vehicles (EVs) is important in reducing these CO_2 emissions. This will significantly reduce fuel consumption, noise pollution, and air pollution. An important area where the introduction of EVs is most beneficial and most common is urban areas (Miles & Potter, 2014).

Today, 56% of the world's population lives in urban areas, around 4.4 billion people. This figure is expected to grow to 68% by 2050 (United Nations, 2018; World Bank, 2024). This increase in population size will increase the demand for transportation within these areas. Public transportation (PT) is crucial to city logistics and supports sustainable urban development (Perumal et al., 2022). Several countries plan to replace their diesel bus fleet with Electric Buses (EBs) in the near future (Y. Liu & Liang, 2021). However, introducing EB fleets (EBFs) is challenging. The introduction of EBFs will couple two essential systems, mobility and energy, together. Both systems are highly congested within urban areas and will continue to do so with the ever-increasing population. The synergy between mobility and energy systems is required to improve the livability of future urban areas (H. Zhang et al., 2020).

Many papers attempt to introduce charging strategies to reduce charging costs (Perumal et al., 2022) or its influence on the energy grid (Wu et al., 2019). However, the synergy between mobility and energy systems is of utmost importance. Recent examples in the Netherlands show multiple public transport operators (PTOs) struggling with deploying EBFs due to insufficient electrical grid capacity and an underestimation of charging times to guarantee operation (NOS, 2023; Omroep Flevoland, 2023; OVPro, 2023).

In the current charging strategies, charging is done at a centralised location and primarily charged at night. However, additional charging during the day is required. Current charging strategies perform this charging at the same centralised location, which causes a considerable number of deadhead trips, trips without passengers and revenue generation (Alamatsaz et al., 2022). This takes considerable time and reduces the total operating time of each bus for every single day. Additionally, the centralisation of charging infrastructure introduces massive demand peaks on the distribution grid and causes power supply fluctuations in the network (Chudy et al., 2022; Mohamed et al., 2017). This research uses opportunity charging as a method to fulfil daily energy requirements before returning to the depot at night. There are several interpretations of opportunity charging in literature. The opportunity charging definition used in this research is a strategy where charging infrastructure is located along the operating route and provides charging during passengers' on- and offboarding and any additional time required for operation (Sebastiani et al., 2016). The location of the charging infrastructure in this research is dispersed throughout the urban area instead of a single charging depot, which is often suggested in literature (Perumal et al., 2022). The dispersion of charging locations allows for the dispersion of electricity demand peaks, thus reducing the grid congestion caused by multiple chargers at a single location.

EBs' charging and charging strategies are influenced by the bus's energy consumption and charging capacity availability at chargers. Decreasing energy consumption will reduce the charging needs of the

EBs, either in terms of charging time or charging capacity. Additionally, increasing the possible time spent at chargers will allow for the reduction of the charging capacity of the chargers and, thus, their load on the grid. Introducing traffic management strategies can enable longer charging times and lower charging capacities. One such strategy, traffic priority, can reduce energy consumption by decreasing the number of acceleration and deceleration actions and decreasing total travel time, increasing the potential charging times without interfering with the timetable (Huan et al., 2019). Traffic priority is a traffic management strategy which prioritizes certain vehicles at intersections or traffic lights and promotes their right of way.

1.1. Research gap

Extensive research has been conducted on optimizing EB charging infrastructure investments, placements, charging planning, vehicle scheduling, and total fleet investments (Alamatsaz et al., 2022; Perumal et al., 2022). However, a critical aspect often overlooked in these optimization efforts is the demand EBs place on the local distribution grid during charging. In contrast, there is substantial literature on the effects of personal electric vehicles (EVs) on residential grids and strategies for mitigating impact—such as neighbourhood charging schedules and the use of centralized parking for dispersed charging (Elnozahy & Salama, 2014; Gong et al., 2012; Rezaee et al., 2013) —only a handful of studies address the specific impacts of EB charging on local distribution grids (Chudy et al., 2022; Dougier et al., 2023; Mohamed et al., 2017; Rogge et al., 2015). These studies often rely on oversimplified grid data, typically based on simple graphical models, and treat overnight and opportunity charging as distinct, unrelated strategies. Moreover, the existing literature predominantly considers scenarios involving multiple chargers at a central location, neglecting the potential role and impact of single chargers in residential neighbourhoods—an aspect this thesis explores. Furthermore, Only one study identified considers the use of congestion tolls, a fee for users of congested roads, as a means to minimize operation costs (K. Zhang et al., 2022), indicating a significant gap in addressing traffic's influence on EB energy consumption and the potential of traffic management as a mitigative measure.

1.2. Research questions

This research aims to provide an integrated approach to opportunity charging implementation. To achieve this objective, the following research question is proposed:

To what extent is the implementation of on-route opportunity charging possible when considering the mobility and energy systems simultaneously?

The following subquestions are answered to solve the main research question:

SQ1: What are current charging strategies for electrical bus fleets?

SQ2: How is grid congestion considered in current charging strategies?

SQ3: To what extent does opportunity charging impact local grid congestion?

SQ4: To what extent can traffic priority for electric buses impact travel time and energy consumption to reduce charging needs and increase charging times?

1.3. Contribution

The research presented in this paper contributes to the literature by providing the following insights:

1. An integrated approach to decision-making containing both the mobility and energy systems by considering the results of two simulation software in decision-making.

2. The impact of on-route opportunity charging on the local distribution grid using real-world consumption data and prediction models.

3. The introduction of GO-E Archetypes allows for generalised conclusions for other systems in the archetype instead of conclusions regarding single systems.

4. Traffic priority is included to investigate its potential in reducing energy consumption and potential reduction of charging capacity and, therefore, the impact of EB charging on local grid congestion.

The contribution of this research in literature is summarized in Figure 1.1. This research presents an integrated approach of decision-making using both the mobility and energy systems. As opposed to the separate approaches found in literature.

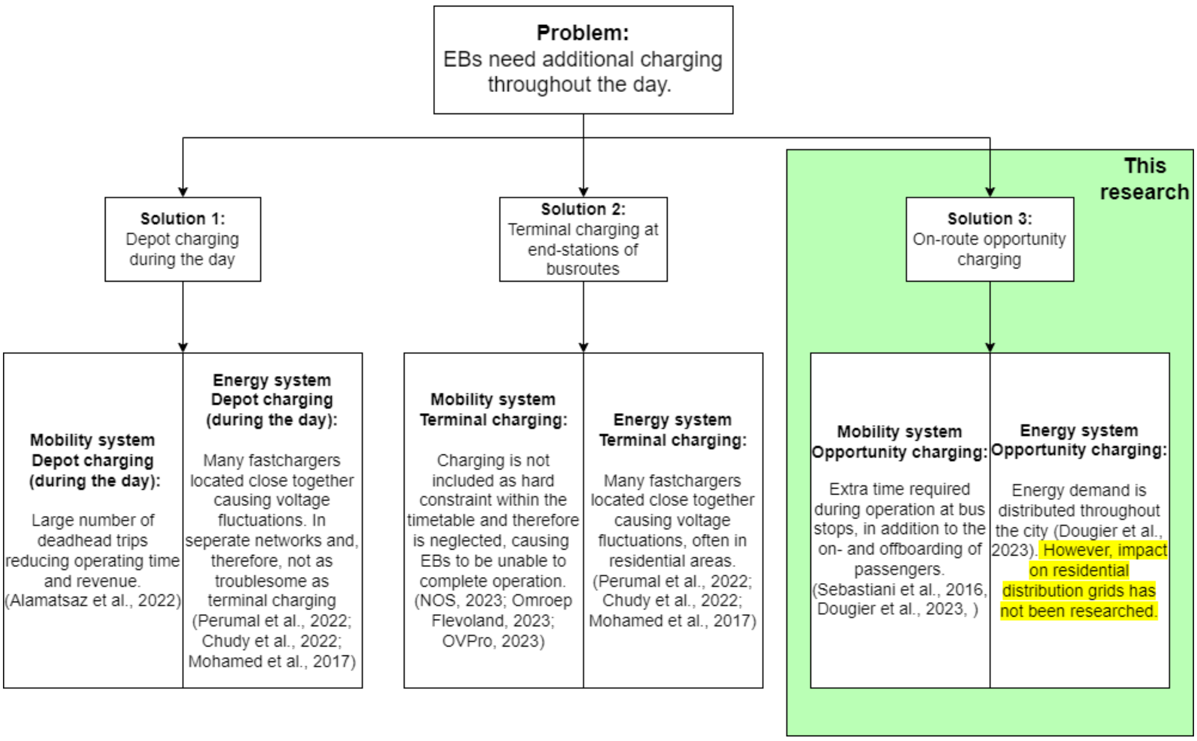


Figure 1.1: The visualisation of the identified gap in literature and position of this research

1.4. Outline

The following chapters are structured as follows. Chapter 2 provides an overview of the state-of-the-art and answers to the first two research questions. Chapter 3 provides an in-depth discussion of the methodology used in this research. Chapter 4 provides the selection of the case study used in this research. Chapter 5 provides the results of the simulations described in the methodology. Chapter 6 provides the discussions of the results obtained, methodologies used and the scientific and societal contributions. Chapter 7 provides a summary of the findings and answers the research questions. Additionally, suggestions for further research are provided.

2 Literature review

2.1. Review methodology

The literature review will be conducted in three separate stages. First, the mobility aspect of EB charging and its design is investigated by searching for current planning and charging strategies. Second, the energy aspect of EB charging and its design is investigated by searching for the impact of EB charging on the grid. The impact on the grid can be expressed in grid congestion, transformer load rates, voltage profiles, and safety. Third, the connection between the mobility and energy aspects of EB service design is investigated by searching for the potential impact of traffic management on charging strategies and their impact on the grid.

2.1.1. Search engines used

The search engines used for this review are Google Scholar and Scopus. Google Scholar is included due to its wide range of sources and available documents. Additionally, Google Scholar includes grey literature. Grey literature is relevant for this research as government documents and policies provide valuable insights into the real-world application of charging strategies. Scopus is included due to its relevance to the topic and quality of search results. However, quality control is essential to ensure valid argumentation. Therefore, several inclusion criteria are used.

2.1.2. Inclusion criteria

To ensure a valid literature review, several criteria were selected to narrow the practical scope of the review. Firstly, the publishing date of the papers is filtered. Only papers published after 2013 will be used. Based on the searches, many results before 2013 focussed on personal vehicle transportation and charging as opposed to bus fleet charging. However, papers cited in the search results which are deemed to be valid are included in the literature review. Therefore, documents before 2013 can be found in the literature review. Secondly, the paper should be peer-reviewed and published in a related journal or book. Lastly, the context of the paper must be similar to the area of interest.

2.1.3. Performed queries

Charging strategies

Table 2 displays the queries performed to investigate the current charging strategies in the literature. The papers used in Section 2.2.1 were found using these queries or found as citations in the resulting papers.

Query	Results Google Scholar	Results Scopus
electric*" AND "bus*" OR "public transport" AND "charg*"	5450	6996
"electric*" AND "bus*" OR "public transport" AND "charg*" AND "starteg*" OR "Plan*"	2560	1307
"electric*" AND "bus*" OR "public transport" AND "charg*" AND "starteg*" OR "Plan*" AND "review"	1750	35

Table 2.1: The performed queries for the investigation of current charging strategies

Grid impact

Table 2.2 displays the queries performed to investigate the impact that bus charging has on the grid. The papers used in Section 2.3.1 were found using these queries or found as citations in the resulting papers.

Query	Results google scholar	Results Scopus
"electric*" AND "bus*" OR "public transport" AND "charg*"	5450	6996
"electric*" AND "bus*" OR "public transport" AND "charge*" AND "energy congestion" OR "net congestion" OR "net aware" OR "grid congestion"	1340	4
"electric*" AND "bus*" OR "public transport" AND "charg*" OR "recharge" OR "opportunity charg*" AND "energy congestion" OR "net congestion" OR "net aware" OR "grid congestion" AND "optim*"	41	5 (title, abstract, keywords) 259 (all fields)

Table 2.2: The performed queries for the impact of charging on the grid

Traffic management in charging strategy

The review for traffic management in charging strategy was run using the same queries listed in 2.2, which means that resulting papers were scanned for the inclusion of traffic management. No precise results were attained. After which, the queries in Table 2.3 were performed. Of the results, only a single paper was identified that integrates traffic management with charging strategy (K. Zhang et al., 2022)

Query	Results google scholar	Results Scopus
"bus*" OR "public transport" AND "charg*" AND "traffic management" OR "priority"	3640	582
"bus*" OR "public transport" AND "charg*" AND "electric*" AND "strateg*" OR "plan*" AND "traffic management" OR "priority"	1350	65
"bus*" OR "public transport" AND "charg*" AND "electric*" AND "strateg*" OR "plan*" AND "traffic management" OR "priority" AND "sav*" OR "reduc*"	263	32

Table 2.3: The performed queries for the impact of traffic management on charging strategies

2.2. The mobility aspect of EB service design

In the following subsections, the mobility aspects of EB service design are discussed. First, current planning strategies are provided to gain insights into the need to include EB charging in the early stages of planning and design. Second, the current charging methods and strategies are discussed to gain insights into the options available to PTOs. Third, the current methods of determining bus energy consumption are provided to gain insights into the calculation approaches of energy consumption and how this is included in the current design.

2.2.1. Current bus planning strategies

The planning of bus lines and their charging strategies follow several steps before the actual deployment of the fleet can be realised. Decision-making ranges from long-term investments such as infrastructure to short-term decision-making to ensure day-to-day operation follows the pre-specified timetable. Perumal et al., 2022 provide an overview of the different stages of planning, shown in Figure 2.1. Strategic planning often regards higher costs but has a more significant impact on the total operation costs, while tactical planning and operational planning have a lower impact on total operation costs. However, high-level strategies are impossible to complete unless the tactical and operational planning actively support the strategies (Ibarra-Rojas et al., 2015). Figure 2.2 provides an overview of the interconnectedness of the planning of bus operations.

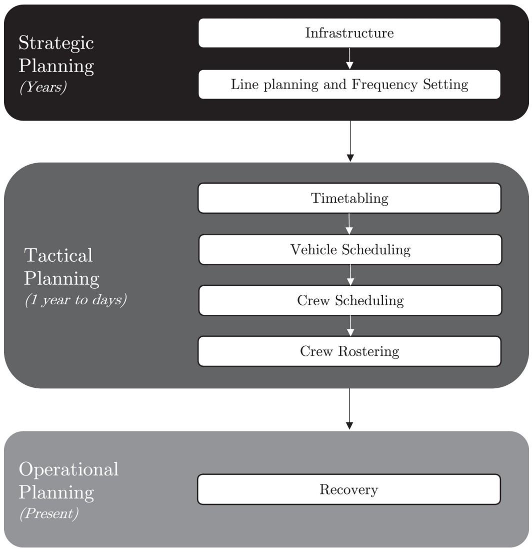


Figure 2.1: A simplified overview of the planning stages in bus operation (Perumal et al., 2022)

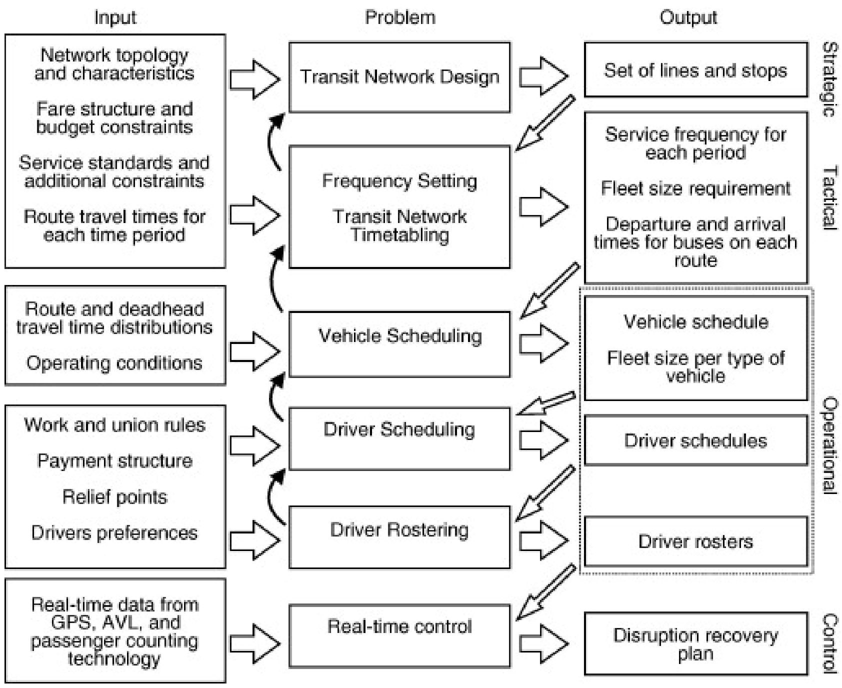


Figure 2.2: The interconnectedness of bus operations (Ibarra-Rojas et al., 2015)

As seen in Figure 2.2, every step within the planning process impacts the preceding and following steps. The figure describes the generalised process for diesel-powered vehicles. However, introducing battery-powered vehicles requires the integration of charging in multiple steps within the process. The introduction of charging electric buses relates to all aspects of bus service design.

Current bus service design

Ibarra-Rojas et al., 2015 provide a clear overview of existing literature up until 2015 describing service design approaches. Many bus service providers optimize and design their systems based on a single or multiple objectives. Table 2.4 provides a summary of the most important objectives used to determine the effectiveness of service design. As the table suggests, the most important determinant of design is the total costs experienced for the system. Additionally, travel times are an important determinant as well as an objective to minimize.

Travel time can be incorporated into the costs using the value of travel time. However, the value of travel time is difficult to estimate. Wardman et al., 2016 provide an overview of 389 studies containing 3109 estimations of values of travel time. Values of travel time differ based on, among others, trip destination and goal, method of transportation, demographic, and trip characteristics. Travel time should, therefore, carefully be considered whether an accurate valuation for the context of the research is available before adding the costs of travel time into the system design.

Design level	# of papers	Most frequent objectives (in order of frequency)
Strategic (Transit Network Design)	45	Min total users' and operators' costs, Min total travel time, Min unsatisfied demand, Min walking distance, Max number of direct trips
Tactical (Frequency setting)	22	Min weighted sum of waiting time and travel time, Min operator costs, Min unfulfilled demand, Min bus runs
Tactical (Timetabling)	27	Min total passenger waiting time, Min total travel time costs, Max number of synchronizations, Min deviations from the original timetable, Min user inconvenience
Tactical (Vehicle scheduling)	18	Min fleet size, Min vehicle costs, Min delays (costs), Min operational costs
Tactical (Driver scheduling)	21	Min duty costs, Min number of shifts, Min inactivity times, Min soft-constraints violation
Tactical (Driver rostering)	6	Min drivers costs, Min overtime, Min penalizations, Max global driver welfare

Table 2.4: Summarization of the most important objectives within the planning of bus fleets, adapted from Ibarra-Rojas et al., 2015

The introduction of electrical bus fleets and their charging will impact almost every stage in the operations planning process, from the planning of charging infrastructure, which belongs to the strategic planning phase, to the scheduling of charging periods, which belongs to the tactical planning phase, to the real-time control of the charging systems, which belongs to the operational phase. Therefore, a careful consideration of charging methods and strategies is required.

2.2.2. Current charging methods and strategies

Employing a fleet of EBs requires charging. There are four major charging technologies in use (Häll et al., 2019; J. Q. Li, 2016; Pelletier et al., 2019): plug-in chargers at bus depots, often characterized by lower charging capacities; fast plug-in or pantograph chargers at bus depots or bus stops, often characterized by fast charging and mainly used for in-operation charging; contact lines or inductive (wireless) chargers for recharging during stops or driving; battery swapping.

A recent literature review by Alamatsaz et al., 2022 provides a list of advantages and disadvantages of the four technologies, shown in Table 2.5. Deadhead trips, mentioned as a disadvantage to depot charging, are trips made by revenue-gaining vehicles that do not accept passengers. As used in this example as trips to and from the depot during operation (Alamatsaz et al., 2022).

Charging Technology	Advantages	Disadvantages
Depot charging	Multiple charging level Providing V2G configuration High efficiency Less grid loss No need to lease the property around service area The upfront capital cost is often cheaper	Batteries' lifetime will decrease due to V2G operation Long recharging time Increase the number of deadhead trips to/from the depot Larger battery packs, more weight and cost Restrictions on placing bus routes due to EB's travel range limitation and deadhead trips to/from depot
Fast charging	Less recharging duration Cover longer bus routes compared to depot charging Little time loss for recharging during operation Require smaller batteries	Voltage instability High cost of fast charging infrastructure Difficulty of placing fast chargers in dense cities
Wireless charging	Recharging process is safe and convenient No need for socket and connector Capability of charging while moving	Huge investment cost for establishing infrastructure Low range of power transmission Weak power transfer
Battery swapping	Fully charged batteries replaced in a short time Prevent the battery capacity and lifetime fade by slow charging Provide V2G configuration to balance the grid	More expensive than conventional buses due to ownership and rent of large battery swap stations Requires a large budget for buying batteries Requires a large area for swapping batteries and their equipment

Table 2.5: The advantages and disadvantages of EB charging methods (Alamatsaz et al., 2022)

The advantages and disadvantages shown in Table 2.5 describe technology-specific issues. However, Perumal et al., 2022 suggests six problems related to high-level issues with the introduction of EBFs: Investments in charging infrastructure, the costs associated with the equipment and installing of infrastructure and how to balance availability; Placement of charging infrastructure, the costs associated with the effective placement of chargers throughout the network to ensure sufficient energy supply;

Investments of bus fleets, the costs associated with the purchasing of EBs and batteries; Electric vehicle scheduling, assigning EBs to a set of timetables to ensure a sufficient service level; Charging scheduling, optimizing the charging costs based on real-time electricity prices and power loads available; Integrated EB planning, integrating required technologies and planning problems with existing requirements such as line planning, timetabling and crew scheduling.

The literature review of Perumal et al., 2022 provides an overview of recent literature and their relation to the previously stated six main problems. The results are shown in Table 2.6.

Author(s)	**Problem**					
	Investment of charging infrastructure	Placement of charging infrastructure	Investment of electric bus fleet	Charging scheduling	Electric vehicle scheduling	Integration with line planning
Haghani and Banihashemi, 2002					x	
H. Wang and Shen, 2007					x	
Chao and Xiaohong, 2013			x		x	
J. Q. Li, 2013					x	
Reuer et al., 2015					x	
Wen et al., 2016					x	
J. Q. Li, 2016			x			
Adler and Mirchandania, 2016					x	
van Kooten Niekerk et al., 2017					x	
Kunith et al., 2017		x	x			
Xylia et al., 2017	x	x	x			
Z. Liu and Song, 2017		x	x			
Leou and Hung, 2017				x		
Chen et al., 2018	x		x			
Rogge et al., 2018	x		x		x	
Yang et al., 2018				x		
Pelletier et al., 2019	x		x			
Messaoudi and Oulamara, 2019				x	x	
Houbbadi et al., 2019				x		
Islam and Lownes, 2019			x			
Janovec and Kohání, 2019					x	
L. Li et al., 2019		x			x	
Jahic et al., 2019				x		
Y. Liu et al., 2019	x		x		x	
Iliopoulou and Kepaptsoglou, 2019		x				x
He et al., 2019	x	x	x			
An et al., 2020	x	x				
Tang et al., 2019					x	
Yao et al., 2020			x		x	
T. Liu and Ceder, 2020	x				x	
Perumal et al., 2021					x	x
J. Wang et al., 2020			x			
Bagherinezhad et al., 2020				x		
Abdelwahed et al., 2020				x		
Olsen et al., 2022					x	
Rinaldi et al., 2020					x	
Zhou et al., 2020				x	x	
Teng et al., 2019					x	x
Olsen and Kliewer, 2020					x	
Ke et al., 2020				x		
X. Li et al., 2020	x		x	x	x	
Alwesabi et al., 2020		x	x			
He et al., 2020				x		

Table 2.6: Results of the literature review of Perumal et al., 2022

For the application to this research, the most relevant papers are those combining charging scheduling alongside electric vehicle scheduling. Only three papers listed contain such a combination: Messaoudi and Oulamara, 2019, Zhou et al., 2020, and X. Li et al., 2020. The work by Messaoudi and Oulamara, 2019 provides a mathematical optimization model to provide a feasible assignment of services, allocation of parking places at the depot and related charging schedule. It aims to minimise the number of buses used and afterwards minimise charging costs. However, the research provides sub-optimal results due to its complexity, even for small instances. The research provides relaxed optimalities for different scenarios and reduces some blocking constraints to achieve lower-bound optimalities. The optimization model provides an example of the ability to reduce battery capacity with a coordinated planning of charging during operation. Further research suggestions include the revisiting of the model to complete the computation of optimalities.

Zhou et al., 2020 provide a mathematical optimization model for a charging schedule based on a mixed bus fleet consisting of electric and diesel-powered vehicles. The results of the paper show a decrease of 7%-13% in charging costs. However, the paper does assume constant energy consumption and the impact on battery service life is not considered. Additionally, only a single depot is used.

X. Li et al., 2020 provide a mathematical optimization model to minimize the total costs of the assignment of buses and charging stations. Total costs saved were approximately 3 million Yuan, translating to a cost saving of approximately 400,000 euros for the installation of the total fleet for a transit network of 8 bus lines. Limitations of this research are the neglect of bus travel time variety, the lack of impact of weather and temperature conditions, and the fact that no global optimal solution was reached.

In addition to the papers identified by Perumal et al., 2022, Sebastiani et al., 2016 provide a mathematical model for the allocation of fast chargers at intermediate bus stops within the city of Curitiba in South Brazil. The results, Figure 2.3, show that intermediate charging, also known as opportunity charging, is a practical approach to ensure the operation of EBs. The effectiveness is measured in terms of extra time required at bus stops. The extra time required is the time required for charging which is in addition to the time necessary for boarding passengers. Even with the lowest number of charging station employment, four charging stations shared by six lines, the maximum extra charging time is 15 seconds. Additionally, the paper by Sebastiani et al., 2016 suggests that the introduction of energy availability, or grid congestion, within the model is worthwhile but was not considered in the study. Recent work by Y. Wang et al., 2022 echoes these claims that opportunity charging would reduce annual total operating cost by 13.38% using pantograph opportunity charging and depot charging compared to only depot charging. This includes infrastructure installation, bus purchasing and operating costs.

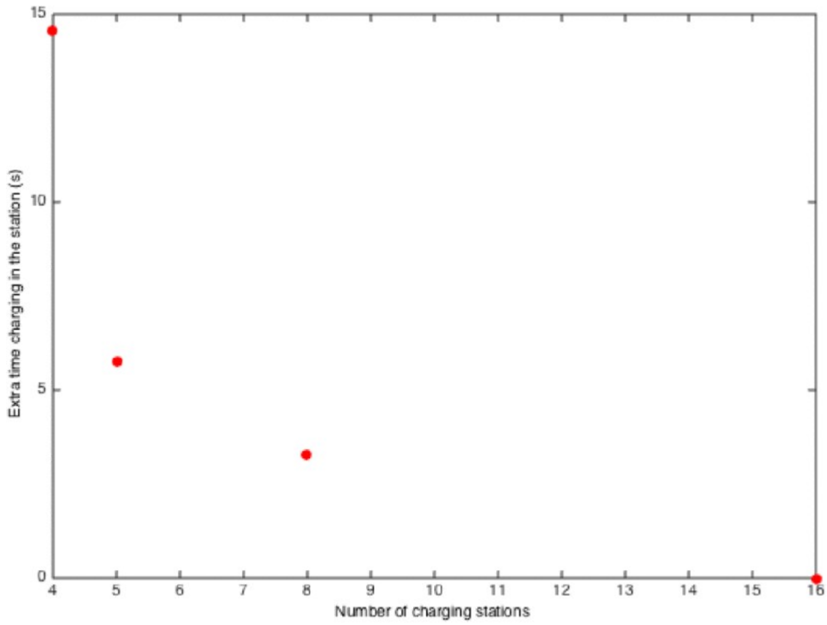


Figure 2.3: Extra time required for opportunity charging based on six bus lines in Curitiba, Brazil (Sebastiani et al., 2016)

Important to note is the introduction of fast chargers in intermediate bus stops within the system. In literature, intermediate charging is often regarded as impossible and is seen as ineffective compared to depot charging. One such example of a paper not including intermediate charging is the work by Abdelwahed et al., 2020. This research provides necessary contributions to the literature by providing a clear comparison between discrete time optimization and discrete event optimization alongside a saving of 16.5% in total charging costs. Coincidentally, within the same research area as this research. However, the model assumes charging is only available at depot stations. The work by Sebastiani et al., 2016 suggests that including intermediate charging should be considered.

P. Li et al., 2023 show the potential of a well-communicated, centralized charging schedule with a total charging cost saving of 53.35% when compared to a decentralized approach where buses return to the depot whenever a low battery percentage is reached. The optimization was performed in Shenzhen, China. It is one of the leading cities in terms of the EB network where 100% electrification has been achieved as of 2017 (P. Li et al., 2021).

Additional considerations

The previously mentioned problems and solution strategies often assume the direct investments related to installing an EBF. But disregard potential operational issues. J. Wang et al., 2020 present an additional strategy associated with the degradation of battery capacity. Their strategy includes assigning different vehicles to different route types based on the current state of the battery degradation. Different route types affect the power output required from the battery, thus causing different capacity degradation. The strategy presented follows a reverse-order matching strategy. It matches the most degraded battery with the lightest load route and matches the least degraded battery with the highest load route. Results of a case study suggest that matching vehicles with routes based on degradation could reduce investments for battery replacements by 20%. In a region with large variations in route characteristics, the reductions could increase to 28%.

Another strategy for reducing total operational costs is Vehicle-to-grid (V2G) capabilities, briefly mentioned in Table 2.5. V2G describes the process of the EV, in this case, the bus, acting as an energy source to the grid (Saldaña et al., 2019). The EB would, therefore, act as a giant battery able to capitalize on the demand and supply of the market. By charging when prices are low and discharging when prices are high, PTOs could gain from an EB system. Manzolli et al., 2022 provide a 2030 prediction with large-scale electrification where the bus system of an 11-bus network with V2G technology in a medium-sized Portuguese city could reduce its operating costs by 38% compared to a scenario without V2G technology. The threshold price of a battery to have profitable V2G capabilities considering battery degradation is 100 €/kWh. Current battery prices are 139 €/kWh, and V2G capabilities are therefore not considered in this study (Statista, 2024).

2.2.3. Current bus energy consumption estimation approaches

Electric buses' energy consumption and, thus, energy demand are highly researched subjects as they provide necessary data for decision-making regarding electric bus fleet installation. The six main problems with electric bus implementation identified by Perumal et al., 2022 shown in Table 2.6 all require data regarding the energy consumption of buses. Investments in charging infrastructure are determined based on the number of chargers needed to supply the energy demand of the electric buses. The placement of charging infrastructure is determined based on the number of chargers and required locations based on the energy demand of the bus fleet. Within the investments in electric bus fleets, the cost of batteries and charging equipment on the bus are large contributors to the total costs. The charging and electric vehicle scheduling are heavily influenced by the time required to charge the energy consumed by the bus fleet. The integration with line planning is similarly influenced by charging times based on energy demand.

The energy consumption of electric bus fleets is often determined using one of three methods (Gallet et al., 2018):

1. Calculation of the average energy demand per unit of distance or time

   The most straightforward approach to determining energy consumption is to calculate a single value of energy consumption for a single bus type on all routes. These values are computed using route distance and total consumption, resulting in an average that is used for future research.

2. Use of a standard driving cycle taken from literature

   This approach uses existing measurements taken from the literature. Authors often choose a driving cycle similar to the conditions of the area in which their case study is located. The energy consumption of the driving cycle from literature is used as energy consumption data for their model or simulation. De Filippo et al., 2014 provide an example of using driving cycle tests performed by bus manufacturers to build a simulation predicting energy consumption.

3. Detailed measurements of driving profile

   The last and most realistic approach is measuring the actual bus energy consumption patterns in the selected case study area. Researchers can develop accurate simulation models by measuring the energy demand at a high temporal resolution. Sinhuber et al., 2012 developed an energy consumption model based on an internet mapping service. Geocoordinates were used to determine the route, after which data regarding speed and stop durations were added to the coordinates. The resulting simulation was tested against real-world data and proven to be accurate. However, the method of obtaining the speed profiles is not described in the research. Ly et al., 2016 develop an energy consumption simulation based on speed data recorded using a GPS tracker in a city in China. This research aimed to determine the feasibility of different battery arrangements and charging techniques. However, no thermal or ageing characteristics were included.

The detailed measurements of real-life operations are logically the most accurate availability of energy consumption information. However, the average energy demand per unit of distance or time is often used in strategic planning for bus line operations. This is due to its ease of use and computational ease. The resulting values of energy consumption do not accurately reflect reality by ignoring traffic conditions, route characteristics, and auxiliary power draw (such as heating) (Gallet et al., 2018).

Many bus service providers optimize and schedule their service to minimize aspects of operation, such as total costs and travel times. However, with the introduction of electric buses, charging is required. In existing decision-making, charging requirements for buses are considered in terms of infrastructure placement, charging scheduling and ensuring an acceptable SoC. The energy requirements are often based on simplified values such as averaging. However, operating conditions and constraints of the local grid are usually disregarded and not included in the decision-making.

2.3. The energy aspect of EB service design

Introducing an EB service requires the inclusion of charging and its impact on the local distribution grid. The following subsection provides the current considerations in optimization and simulation models regarding the impact that EB charging has on the distribution grid. It highlights the need for consideration using current congestion levels and provides the current practices to include the impact on the grid in service design.

2.3.1. Current considerations of impact on the grid in decision-making

The charging of EBFs requires substantial power demands, ranging from 50 kW for plug-in chargers to 500 kW fast-chargers (He et al., 2020). The peaks in power demand will unquestionably have a large impact on the local electricity grid. Congestion on the electricity grid is currently a huge issue within the Netherlands, as seen in Figure 2.4.

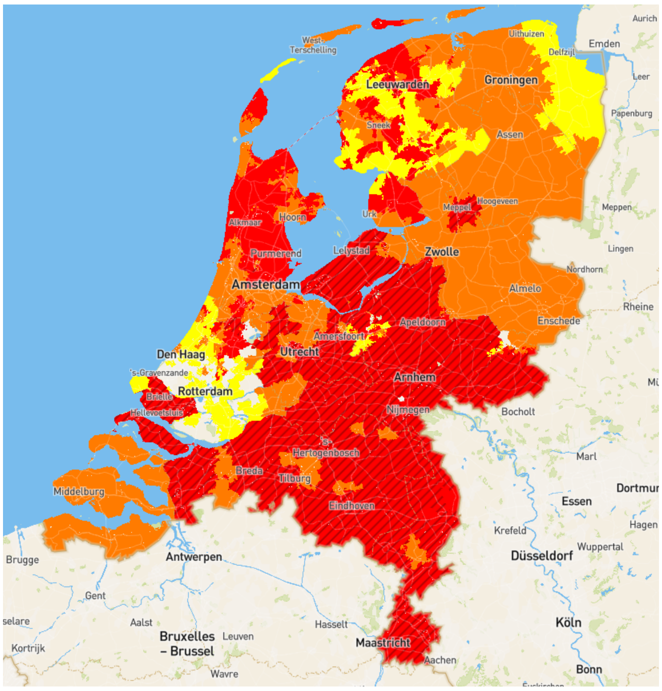


Figure 2.4: The current congestion levels in the Netherlands for energy demand, red = capacity reached for foreseeable future, orange = capacity reached, but capacity become available soon, yellow = limited capacity available, uncoloured = capacity available (Netbeheer Nederland, 2023)

The connection between EB operation and impact on the grid is often implemented into either one of two methods (Wu et al., 2019):

1. The introduction of variable tariffs in the charging costs.

   The optimization objective often mentioned in the papers provided in Table 2.6 is the reduction of charging costs. In some cases, such as Abdelwahed et al., 2020, the impact on the network is assumed to be directly related to the variable price of charging. Abdelwahed et al., 2020 state in their research that a reduction of charging costs by 16,5% directly correlates to a reduction of grid load by 16,5%, without any further research into the correlation between cost reduction and effect on the grid. Additionally, there is no mention of the total impact on the grid. Wu et al., 2019 introduce a bi-level model where bus operation is optimized to minimise net operational costs while facilitating grid congestion relief. Their optimization model, based on a combination of 8 bus routes in Shenzhen, China, reduced charging costs by 25,88% and reduced power loss in the grid by 7,2%. This example shows why the direct correlation between charging costs and the reduction of grid load is incorrect.

2. Integration of EV loads and capacity into an intelligent energy system.

   The application of personal EVs into the smart grid as both demand and supply have been investigated for years, (Tan et al., 2016). Prencipe et al., 2022 provide a mathematical model study for the city of Delft with a charging station of shared EVs where the V2G options of the parked EVs counteract the consumption of the EV driving. The cost of energy varies throughout the day, and the system allows for charging parked EVs when costs are low and selling this energy when costs are high. The sales of energy from the parked vehicles made up for the costs of the power consumed by the EVs in use. The EVs are only in use during 12% of the day. The other 88 % of the day is when they are used for revenue generation. The total operating costs of the system resulted in a positive value of around 36 euros per day. This includes all the costs of driving the shared EVs during the day.

EV integration into the smart grid has been proven to work beneficially. However, research into integrating EBFs into the grid is limited (Wu et al., 2019). In a more recent study, Y. Liu and Liang, 2021 provide a three-layer management approach to optimize bus charging strategies while retaining local voltage quality by integrating EB charging with the smart grid. First, the approach estimates the energy consumption of the EBs. Second, the approach estimates the energy flow in the network required for the network's operations. Third, the impact on the network is considered in order to reevaluate the charging strategy. Figure 2.5 displays the connection between the three layers in the management approach. The management approach consists of a feedback loop where the operating and charging schedule of the EBF is communicated with the distribution system, which returns the operating conditions of the distribution grid with the expected load of the EBF back to the bus operator. The condition of the distribution grid might impact the planning of the EBF due to the availability of charging capacity. This feedback loop ensures that the charging of the EBF stays within the possibilities of the energy network.

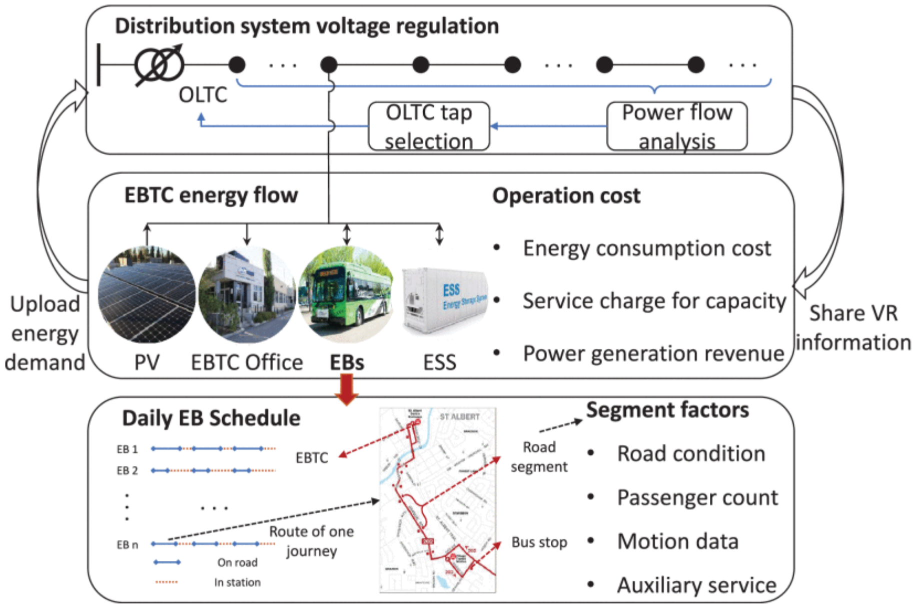


Figure 2.5: The integration of EBs into the smart grid and optimizing for operational costs (Y. Liu & Liang, 2021)

This study provides an approach to minimize operating costs. The operating costs are minimized under the condition that voltage levels should not increase or decrease exceeding specified thresholds. However, there is no inclusion of any existing grid loads, such as households, which have widely varying consumption patterns.

The impact of charging on transformers over time

The introduction of charging stations, especially opportunity chargers, requires the consideration of existing grid loads to which the charging loads will be added. Current studies mainly focus on the impact of PEVs on the local grid.

Gong et al., 2012 present the impact on lifetimes that overloading the system with charging of PEVs has. The research compares five different scenarios: simultaneous charging at 7 pm, simultaneous charging at 12 am, randomized charging strategies with 30-minute intervals, randomized charging strategies with 15-minute intervals, and evenly average charging where the load is dispersed between 7 pm and 6 am. The simulation results show that the collective charging of PEVs has an enormous effect on the lifetime of mid-to-low-voltage transformers. Collective charging can reduce the lifetime to mere days compared to the expected lifetime of over 40 years. The simulation assumes charging capacities of 6.6 kW per vehicle and penetration grades of 70-100%. Penetration grade means the percentage of households owning a specific item, such as PEVs or PV modules. This study displays the impact of charging on local residential grids and the lifetime of the connected transformers. Voltage levels stay within acceptable levels (95%-105%) only with a penetration grade of 8%. The chargers of EBs have larger power demand peaks than those of PEVs. Therefore, the impact of opportunity charging on transformers' lifetime should be accounted for.

Elnozahy and Salama, 2014 present the percentage of low-to-mid-voltage transformers that require upgrades based on PEV penetration grades and consumption patterns within residential areas. The existing residential loads are simulated using six representative load curves. The demand curves of hourly data for 365 days were clustered, and six representative load curves were selected based on a c-means clustering algorithm. Each representative load curve has a probability of occurring. Figure 2.6 displays the six representative curves used to generalize consumption patterns throughout 365 days. Each representative load curve corresponds to different times of year. For example, the red line is a day in the middle of summer when little energy is consumed, and the dark blue line is a day in the middle of the winter when most power is consumed.

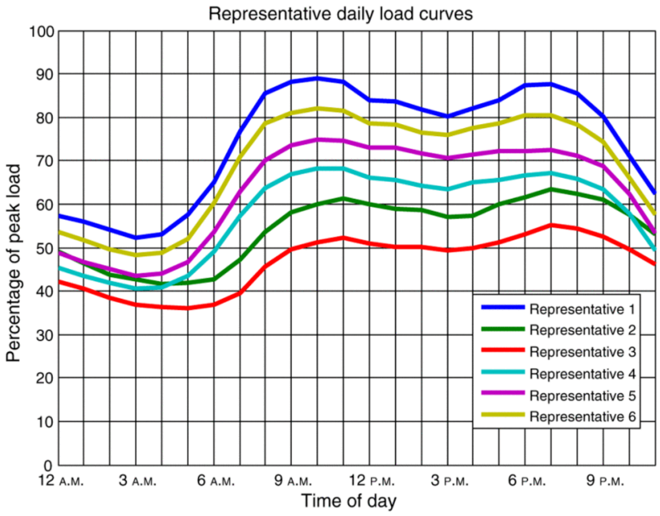


Figure 2.6: Six representative curves of load profiles in 365 days used in research by (Elnozahy & Salama, 2014)

Additionally, commercial loads were gathered, and a single load curve was generated, as commercial loads have low variability (Elnozahy & Salama, 2014). The results suggest that more than 95% of all transformers require upgrades at a PEV penetration grade of 40%. Similar to Gong et al., 2012, the impact of higher-powered EB opportunity chargers could increase the detrimental effect on the transformer upgrade threshold.

Rogge et al., 2015 present a case study of the city of Muenster with 76 service trip types, 1,588 service trips per day and a daily driving distance of 27,000 km. The energy requirements of the EBs are based on route- and demand characteristics with assumptions of average speed and average waiting times. The chargers implemented are 500kW conductive chargers. However, these chargers are plug-in chargers and would be infeasible for passengers on- and offboarding, as presented in the research. The charging requirements are translated into a moving average power profile. However, the power profile is not used to investigate the impact on either the mid-to-low-voltage transformer or the Voltage in the system.

Mohamed et al., 2017 present a case study of the city of Belleville in Canada, where six different scenarios of EB charging are investigated and linked to transformer size and impact on the lifespan of the transformers. The scenarios are subdivided into flash charging, opportunity charging and overnight charging. Flash and opportunity charging both benefit from on-route charging. However, flash and opportunity charging differ in battery size, charging capacities and range. Flash charging has a higher charging power but a smaller battery size and range. The results indicate varying charging needs and, therefore, carrying impact on the local grid for the scenarios. Essential conclusions are that the charging frequency is susceptible to the charger's power and less sensitive to battery capacity. Figure 2.7 displays the charging strategies' resulting charging frequency and power draw.

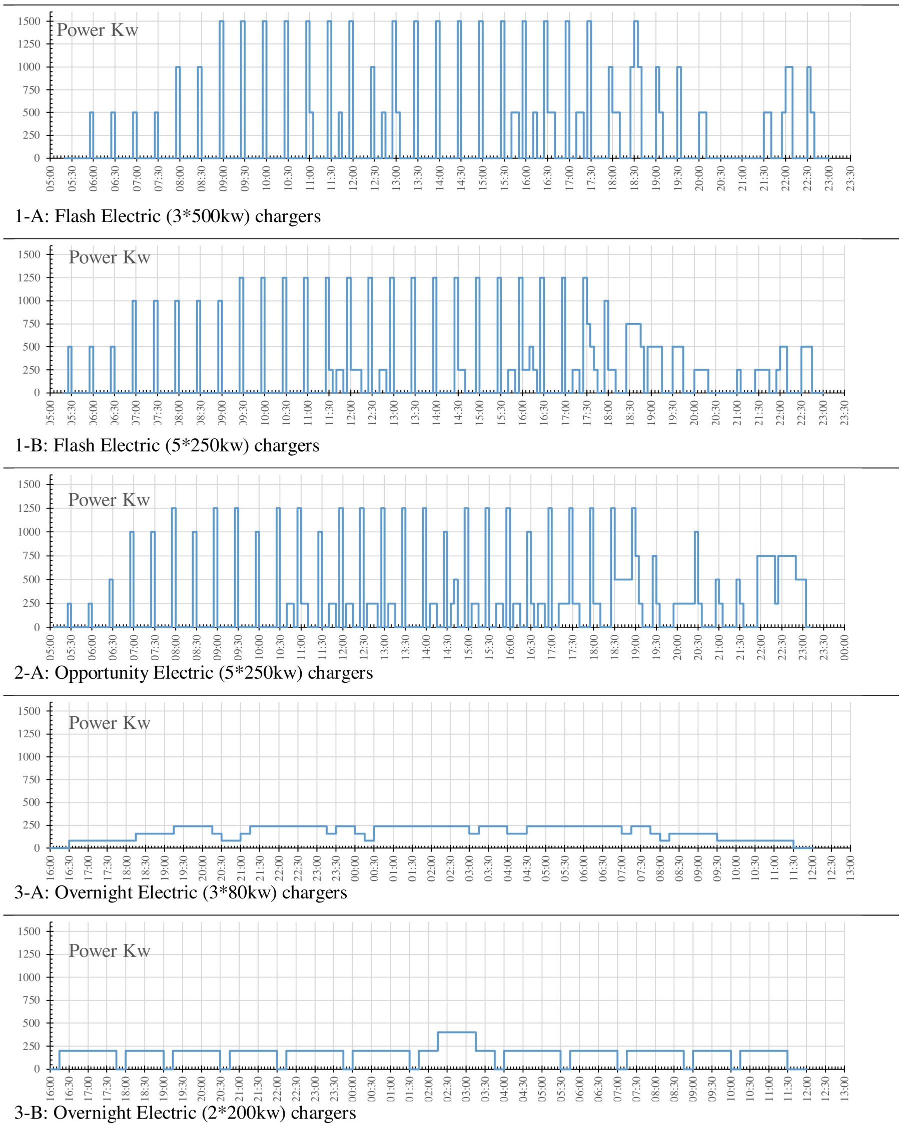


Figure 2.7: The charging profiles of different charging strategies by Mohamed et al., 2017

The different charging profiles require different transformer configurations. Flash and Opportunity charging requires transformers with 5 to 6 times larger capacities than overnight charging. Additionally, the average demand is higher than the overnight charging. However, the load factor is significantly lower for fast and opportunity charging.

The research compares the lifetime of transformers in a case where no buses are charging on the local grid to the different scenarios. The differences in lifetimes are not significant. This can be attributed to flash and opportunity charging occurring only for a very limited time and the overnight charging occurring during off-peak hours. However, the opportunity chargers significantly negatively impact the lifetime of load tap changers (LTCs). LTCs control the voltage that runs through the system by connecting or disconnecting parts on the high-voltage side of the transformer. The LTC degradation is caused by the need to change the voltage availability in the system due to the high power demand spikes of flash and opportunity charging. It's about ten times more often than overnight charging. Additionally, flash and opportunity charging cause a daily loss of energy 30% greater than the overnight charging scenarios. Figure 2.8 displays the voltage profiles in the system under different scenarios. Operationally, flash and opportunity charging have the advantage in terms of charging requirements and disruptions of timetabling. However, overnight charging is much preferred for grid transformer LTC degradation and energy loss.

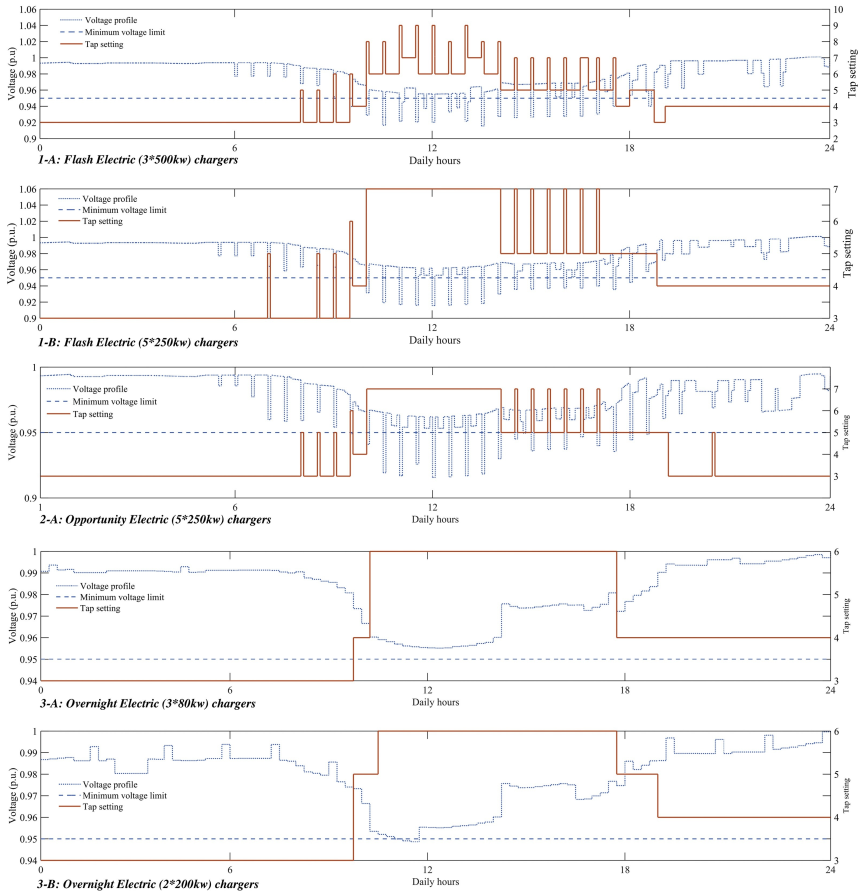


Figure 2.8: The voltage profiles of the scenarios by Mohamed et al., 2017

Chudy et al., 2022 present a case study of 14 fast chargers at a depot in Poland and the effect on the voltage levels in the local distribution grids. The fast chargers employed had a rated capacity of 80 kW. The energy demand data of the EBs was based on real-life measurements at the depot. Deploying 14 fast chargers caused the voltage fluctuations from the transformer to exceed local guidelines. Therefore, a large collection of fast chargers at a single depot was deemed impossible.

Dougier et al., 2023 presents a case study of a city in France where on-route charging is used to reduce battery sizes. A PV system is installed to reduce the impact of the charging of the EBs on the local distribution grid. The battery consumption of the EBs is compared to the PV production. The energy consumption calculations are based on an existing physical consumption model by Hjelkrem et al., 2021. The PV system was deemed insufficient to support the charging of the EBs. However, no further impact on the local distribution grid was researched.

2.4. Connecting mobility and energy aspects of EB service design

The following subsection provides an investigation into the connection between the mobility and energy aspects of EB service design. The connection can be found in traffic management, where changes in the mobility systems for the EBs change the charging requirements and costs, connecting the two aspects of EB service design.

2.4.1. Traffic management in charging strategies

Traffic management in charging strategies is meant to allow the EBs to reach their destinations faster, resulting in lower consumption due to a decrease in acceleration and deceleration requirements (Huan et al., 2019) and allowing the buses to have more time at bus stops to charge while retaining service level. Execution can be done by using priority lanes for buses or increasing the green time at traffic light intersections. Currently, limited research is available on integrating traffic management and charging strategies. Many papers include volatile travel times, which significantly change during the day (Ibarra-Rojas et al., 2015). However, this volatility can be relieved using traffic management and priority for the EBs. (K. Zhang et al., 2022) provide a model of minimizing operation costs using both variable charging prices as well as congestion tolls. Congestion tolls are extra fees incurred by users on specific roads at specific times. Current congestion tolls are predetermined and do not adjust to real-time traffic situations. Research suggests the ability to adapt these to real-time tariffs to accurately control traffic (Tomizuka, 1997). The inclusion of congestion tolls in the research by K. Zhang et al., 2022 provide some inclusion of traffic management into charging strategies but does not actively intervene with travel times.

2.5. Literature review conclusion

In conclusion, extensive research has been conducted on optimizing EB charging infrastructure investments, placements, charging planning, vehicle scheduling, and total fleet investments (Alamatsaz et al., 2022; Perumal et al., 2022). However, a critical aspect often overlooked in these optimization efforts is the demand EBs place on the local distribution grid during charging. In contrast, there is substantial literature on the effects of personal electric vehicles (EVs) on residential grids and strategies for mitigating impact—such as neighbourhood charging schedules and the use of centralized parking for dispersed charging (Elnozahy & Salama, 2014; Gong et al., 2012; Rezaee et al., 2013) —only a handful of studies address the specific impacts of EB charging on local distribution grids (Chudy et al., 2022; Dougier et al., 2023; Mohamed et al., 2017; Rogge et al., 2015). These studies often rely on oversimplified grid data, typically based on simple graphical models, and treat overnight and opportunity charging as distinct, unrelated strategies. Moreover, the existing literature predominantly considers scenarios involving multiple chargers at a central location, neglecting the potential role and impact of single chargers in residential neighbourhoods—an aspect this thesis explores. Furthermore, Only one study identified considers the use of congestion tolls, a fee for users of congested roads, as a means to minimize operation costs (K. Zhang et al., 2022), indicating a significant gap in addressing traffic's influence on EB energy consumption and the potential of traffic management as a mitigative measure.

An integrated approach to opportunity charging implementation considering the mobility and energy systems and including traffic management is developed in this thesis. The methods to achieve this integration are discussed in Section 3.

3 Methodology

The following sections discuss the different approaches to answering the research questions stated in Section 1.2. The methods are summarized in Table 3.1.

To what extent is the implementation of on-route opportunity charging possible when considering the mobility and energy systems simultaneously?		
Subquestion	**Method**	**Sections**
1. What are the current charging strategies for electrical bus fleets?	Literature review Interviews	2.2.1, 2.2.1, 2.2.2, 2.2.3
2. How is grid congestion considered in current charging strategies?	Literature review Interviews	2.3.1
3. To what extent does opportunity charging impact local grid congestion?	Case study Sumo Gaia	3, 4.1, 5, 6, 7
4. To what extent can traffic priority for electric buses impact travel time and energy consumption to reduce charging needs and increase charging times?	Case study Sumo Gaia	2.4.1, 3, 4.1, 5, 6, 7

Table 3.1: The methods of answering the subquestions

Figure 3.1 displays the approach to answer the questions proposed in Section 1.2. The numbers listed in between brackets are the corresponding subquestion numbers. The figure shows the process of how each research step leads to the next and how this provides an answer to the research questions. The following subsections discuss the methodology in detail.

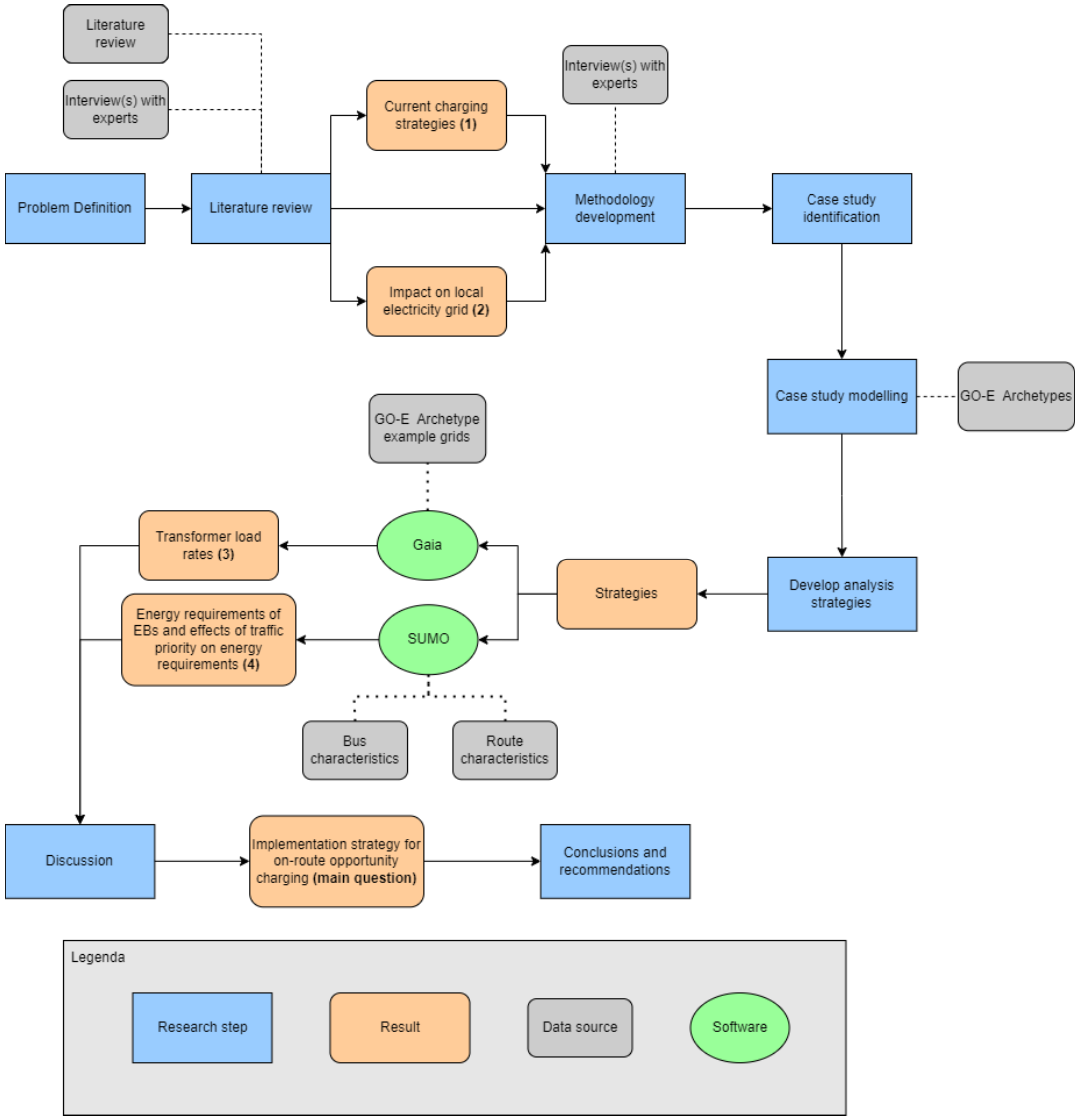


Figure 3.1: The methodology of answering the research questions

As concluded in the literature review in Section 2, there is a lack of research into the connection between mobility and energy systems when developing charging strategies. In order to build this connection, two tools are required, each related to one of the systems. The first tool, related to the mobility system, must be able to investigate the energy consumption behaviour of EBs in traffic. Additionally, the implementation of traffic priority should be achievable. The second tool, related to the energy system, must show transformer behaviour in local distribution grids with the ability to add an opportunity charger to the grid.

The first tool selected to represent the mobility system is the simulation software SUMO (Simulation of Urban MObility), discussed further in Section 3.1. SUMO allows for the development of traffic systems and the inclusion of traffic priority within them. Moreover, an electric vehicle module is available within the software (Kurczveil et al., 2014).

The second tool selected to represent the energy system is the simulation software Gaia, discussed in Section 3.2. Gaia shows transformer load rates based on real-life distribution grid data. The acquisition of the distribution grid data is explained in Section 3.3.

3.1. SUMO

SUMO, is an open-source, highly portable, microscopic and continuous traffic simulation package. It allows researchers, urban planners, and transportation engineers to model various aspects of traffic flow and evaluate the impact of different policies, infrastructure changes, and traffic management strategies. SUMO is used to build the case study network and different strategies. Since SUMO is open-source, many extension modules have been integrated. One such module is the electric vehicle module (Kurczveil et al., 2014). The module introduces electric vehicles and charging stations. Electric vehicles can be configured using the characteristics listed in Table 3.2. Charging stations can be configured according to personal specifications, with configurable charging speeds, times and delays. The charging delays are the number of seconds the bus needs after complete stand-still after which it can start charging. The characteristics of the charging device are dependent on the charging technology chosen. The charging technology options are shown in Section 2.2.2.

Name	Description
Maximum battery capacity	Maximum battery capacity
Maximum power	Maximum power which the vehicle can reach
Vehicle mass	Vehicle mass
Front surface area	Front surface area
Air drag coëfficient	Air drag coëfficient
Internal moment of inertia	Not a moment, but the (equivalent) mass of internal rotating elements
Radial drag coëfficient	Radial drag coëfficient
Roll drag coëfficient	Roll drag coëfficient
Constant power intake	Average (constant) power of consumers
Propulsion efficiency	Drive efficiency
Recuperation efficiency	The efficiency of regenerative braking
Stopping threshold	Minimum velocity to start charging

Table 3.2: The required vehicle characteristics of SUMO simulation

The simulation will provide the output as shown in Table 3.3

Name	Description
time	Current timestep
id	id of vehicle
energyConsumed	energy consumption in this timestep in Wh
totalenergyConsumed	the total energy consumed in the trip up until this timestep
totalEnergyRegenerated	the total energy regenerated by regenerative braking up until this timestep
actualBatteryCapacity	energy content of the battery in this timestep
maximumBatteryCapacity	Max energy capacity of the battery
chargingStationId	If the vehicle is exactly at a charging station, this value is the id of the charging station, in other case, is NULL
energyCharged	Charge received in the current time step from a charging station (Only != 0 if vehicle is exactly at a charging station)
energyChargedInTransit	Charge that a vehicle in transit received in the current time step from a charging station
energyChargedStopped	Charge that a stopped vehicle received in the current time step from a charging station
speed	Speed of vehicle in this timestep
acceleration	Acceleration of vehicle in this timestep
x	absolute position x of vehicle in the map
y	absolute position y of vehicle in the map
lane	id of the lane that the vehicle is currently on
posOnLane	Position of vehicle on its current lane
timeStopped	Counter with the number of timesteps that the vehicle has remained standing

Table 3.3: The output of SUMO for every timestep

The output shown in Table 3.3 allows for the determination of the following results:

- The total travel time: By using the last timestep that the vehicle appears in the simulation, the total travel time can be determined.
- The total energy consumed per round trip: By using the total energy consumed in the last time step that a vehicle appears, the total energy for a trip can be determined.
- The total energy regenerated with braking: By using the total energy regenerated in the last time step that a vehicle appears, the total energy gained from regenerative braking can be determined.
- The total energy charged by the chargers: By identifying the last time step where the bus gets charged and multiplying that value by the number of chargers. The same charge amount is gained for each charger in this research.
- The total battery charge lost per round trip: The actual battery capacity at the last time steps determines the total energy charge lost by subtracting this value from the starting battery capacity. This includes total energy consumed and all energy charged, both with regenerative braking and opportunity charging.

For every strategy, SUMO is the first simulation to be run. SUMO requires as input the following items:

- The bus characteristics as listed in Table 3.2;
- The route characteristics including charging locations, charging capacities, intersections with priorities, road length and maximum speeds, and traffic volume;

The route characteristics are modelled using manual input. Intersections, road length, maximum speeds and traffic volume are manually added using data from Open Street Maps, Google Street View and real-life visits. Charging locations are determined based on the distance to transformers due to enormous infrastructural investment costs. Installing underground infrastructure ranges in price from lower estimates of €100,000/km to €1,000,000 (Larsen, 2016) to as large as €1,500,000/km to 3,000,000/km (Benmenni, 2021). Even though direct investment costs are not considered in this study, locating opportunity chargers close to transformers is realistically preferred.

As output, SUMO will provide data regarding the energy requirements at every time step for every charging location. This energy requirement will form the input of the energy system simulation software. In addition to energy requirements, SUMO allows for the implementation of traffic priority. Traffic priority is an important factor in the connection between mobility and energy systems by introducing the potential to reduce the total energy consumed by reducing the number of acceleration and deceleration actions (Huan et al., 2019) and the potential to charge for longer periods of time without changing the timetable.

3.1.1. Traffic priority in SUMO

An important aspect of the selection of SUMO is the possibility to include traffic priority. Traffic priority concerns the right of way of traffic at intersections. Traffic priority for EBs at intersections will reduce the consumption of energy by the EBs by reducing the number of accelerations and decelerations that are required to complete the journey of the electric bus (Huan et al., 2019). Multiple cities have priority for PT in place. However, this is mainly implemented to reduce travel times for PT users. This research focuses on energy requirement reductions and potential increases in charging times without interrupting service levels (Cheng et al., 2023). Erdmann and Krajzewicz, 2011 provide an in-depth explanation of the current intersection modelling that is used within SUMO. Every intersection is configurable in terms of priority and traffic lights.

The base model of an intersection works as follows:

1. The first car to approach the intersection is free to go;
2. If multiple cars approach at (roughly) the same time, normal right-of-way regulations are followed, meaning cars approaching from the right have priority, short turns have priority over longer turns and straight traffic has priority over turning traffic.

3. If multiple cars are coming from a single lane, these cars will follow the leading vehicle. Unless the time between vehicles is greater than the time it would take for another vehicle to pass. If the time for another vehicle is less than the time between vehicles in the current lane, this new vehicle will cross the intersection. The vehicle crossing first when space is available is based on the right-of-way. This step is repeated until all vehicles have passed and a new vehicle approaches.

The base model works as described if every lane has the same priority value. Lanes have configurable priority values. If the priority value is manually changed, it will be taken as leading. Therefore, in the aforementioned model, the lane with the highest priority will be selected first. However, following vehicles in a lane always have priority. The stream will not be broken by the simulation to give way for the prioritized lane. However, if space is available for new vehicles, the ones with priority will always be selected first. Figure 3.2 provides an example of traffic regulations at an intersection. On the left, the blue vehicle follows the leader at the intersection as too little space is available for the red car to join. On the right, the blue car waits as the red car has already entered the intersection after which the blue one arrives (Erdmann & Krajzewicz, 2011).

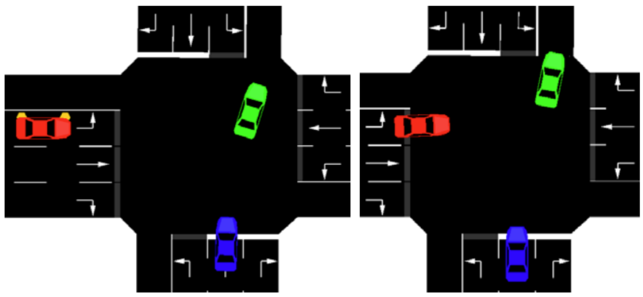


Figure 3.2: An example of intersection regulation in SUMO by Erdmann and Krajzewicz, 2011

In addition to the base traffic regulation at intersections, SUMO includes traffic lights, called the Traffic Regulation Systems (TRS). A TRS can be included at an intersection and its functioning can be configured. The configuration is done by changing the time values of specific green, yellow, and red combinations at the intersection. Figure 3.3 provides an example of a cycle in a TRS system at an intersection in SUMO.

Traffic priority is included in the simulation by increasing the priority values of the lanes on which the bus drives. Additionally, priority in traffic regulation systems is introduced by increasing the total green time of the lanes on which the bus drives.

SUMO provides this research with the energy requirements of operating an EB service. However, this does not include the energy system regarding grid operation. Different simulation software is required for the distribution grid. The software chosen to include the distribution grid is Gaia.

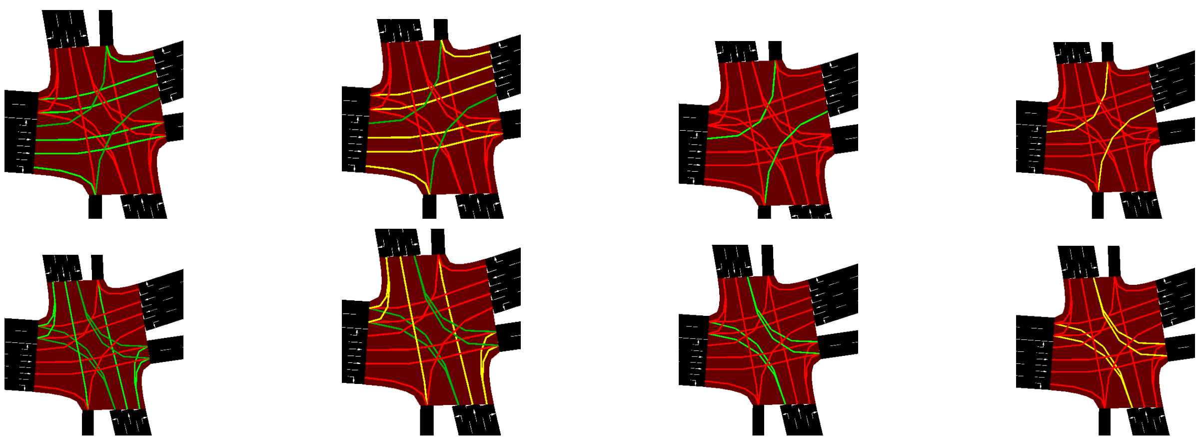


Figure 3.3: The cycle of an example TRS in SUMO

3.2. Gaia

Gaia is a software developed to plan, design and manage low-voltage electricity grids. PGOs can configure their grid in the software and calculate, amongst others, the voltage in the system, the current in the system (in Ampere), the load rate on the mid-to-low voltage transformers (in %) and the safety of the network (Phase to Phase, 2024). The simulation input requires demand profiles of connections and characteristics of the cables used for the connections. Gaia proposes demand functions for every day of the week. However, in most cases, the demand profiles are summarised in three days: a generic weekday, Saturday, and Sunday. The subdivision of a week into a generic weekday, Saturday and Sunday is standard practice for PGOs and, therefore, included as such in Gaia. These demand functions can be configured for every month of the year. For example, in the winter months, the demand profile for a heater would peak around the time people return from work during a generic weekday but would be more consistently in demand during a weekend day. Demand is included in the simulation in one of two ways: either a probability distribution function or a predetermined demand profile. The probability distribution functions represent components (single items such as a dishwasher or PV module) of a connection (such as a house). Components such as PV modules are unpredictable in their production and are, therefore, simulated as distributions. This provides the simulation with the possibility to calculate the 5% and 95% distribution threshold, giving a best and worst-case scenario for the distribution grid. An example of a probability distribution for a household is given in Figure 3.4. Figure 3.4 displays the power demand probability curves of a PV system (red), Heat pump (yellow) and a privacy-protected consumption pattern of this household to not violate privacy laws (green). The examples show that the PV has a higher probability of generating more power in summer and consuming less power in both the heat pump and the protected consumption patterns in summer, compared to winter.

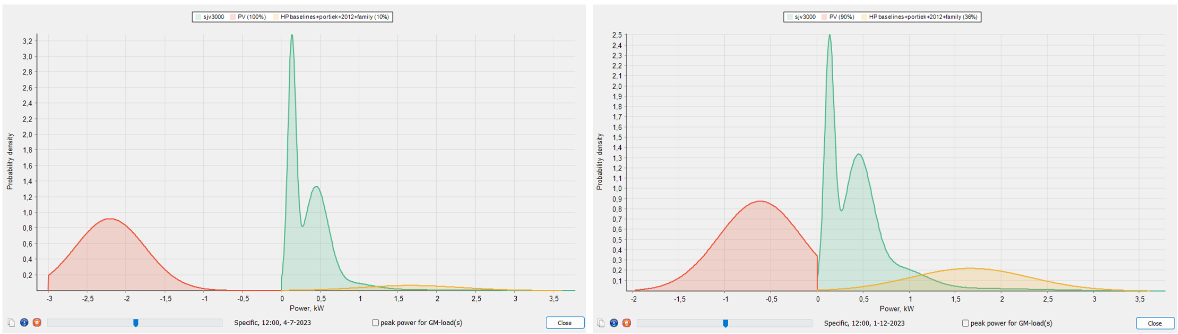


Figure 3.4: The consumption pattern of a household on a generic workday in July (left) and December (right) at 12:00

In addition to the demand distributions, Gaia uses demand profiles to model demand. Demand profiles are predetermined values of component demand over time. The profile ranges in value from 0 to 1, where the ratio is multiplied by the maximum demand of the connection assigned to the profile. For example, a 200 kW charger with a profile value of 0.6 at a given time will exert a load of 120 kW on the connected infrastructure. Figure 3.5 displays an example of a profile for an EV charger for a full week. The peaks of the figure can be attributed to people returning home from work. The valleys in the figure can be attributed to the charger charging during the night and allowing for the reduction in power draw over time due to the battery approaching full capacity. The symmetry in the first five days is attributed to the software using a generalised workday for its calculations, repeated until the weekend.

Using the demand probability distributions and profiles, the simulation calculates the loads in the network every 15 minutes for the three generalised days (weekdays, Saturdays, and Sundays) in the week for every month of the year. The network load is then used to determine the grid quality based on cable usage and rated capacities. The quality of the grid is based on voltage, current, the load rate on connected transformers and the safety of the network.

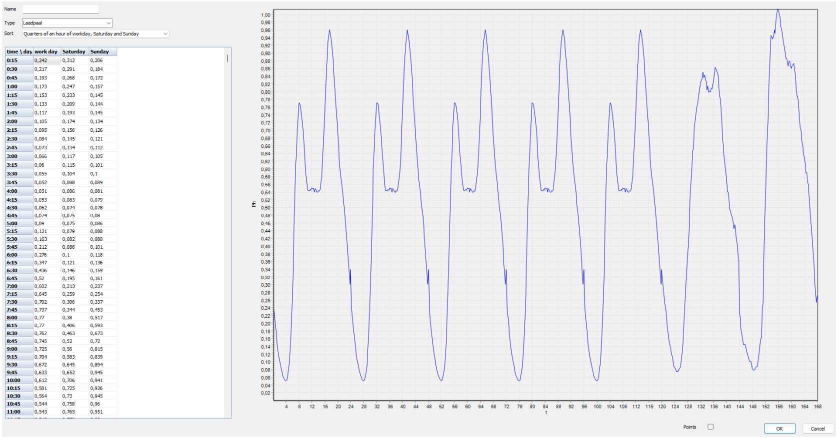


Figure 3.5: The demand profile of an example EV charger for a week

New connections, such as opportunity chargers, can be manually inserted into the grid with a specified demand profile. The opportunity chargers are included in the demand probabilities and resulting grid characteristics. The inclusion of the opportunity chargers is discussed in Section 4.1.6.

Gaia requires a set of connections and consumption patterns to determine the loads on the transformer. Connections and consumption patterns are highly privacy-sensitive information. To allow the usage of real-life data, protection of privacy is required. For this, a collaborative effort of multiple energy— and research-related companies has developed a number of archetypes called GO-E archetypes.

3.3. GO-E archetypes

Gaia uses grid data as input to determine the quality of the grid. To use real-life data for the software in this research, protection of privacy-sensitive data is necessary as energy consumption data is highly private. Within the research project Gebouwde Omgeving Elektrificatie (GO-E), a consortium of energy- and research-related companies developed a methodology of subdividing the Netherlands into 8 different grid archetypes. These grid archetypes have data available because of the introduction of smart grids and smart meters.

The introduction of smart grids has greatly improved the operations of electricity grids in terms of monitoring grid quality and the near instantaneous ability to balance supply and demand (Mahmood et al., 2015). The coordination between operator and consumers allows for the lowering of costs while simultaneously increasing the reliability, stability and resilience of the system (Yan et al., 2013). Smart grids require the installation of two-way communication technologies to monitor and react to demand. One such technology is a smart meter. Smart meters are installed at the connection between households and the grid infrastructure and give both operator and consumer insights into consumption patterns. This allows the operator to track and record electricity usage to support decision-making while providing customers with information to adjust their consumption to reduce their electricity bill. For example, by planning the charging of their PEV during off-peak times (Armoogum & Bassoo, 2019).

The introduction of the GO-E archetypes by the companies is necessary due to the privacy-sensitive nature of energy consumption/grid data. Consumers' privacy has been a topic of discussion since the introduction of smart grids and smart meters in consumer homes. Based on the information communicated through the smart meter malicious attackers could (Armoogum & Bassoo, 2019): estimate the number and types of electrical appliances; estimate the number of residents in a home; gather behavioural knowledge such as whether users are home, and when they leave for both short (work) and longer (vacation) periods at a time; have real-time information about the activities of the user; perform location tracking of the EV, based on usage patterns; gather personally identifiable information about users.

Due to the privacy-sensitive nature of energy consumption/grid data, energy companies are obligated not to share their data and reduce the data records to those necessary to perform their operational tasks (De Nederlandse Overheid, 2012). However, to perform research regarding grid operation and innovations, real data is preferred. Additionally, being able to use generalised assumptions to increase the quality of other grids is beneficial. This need for research possibilities and assumption generalisation is the reason for developing GO-E archetypes.

The GO-E archetypes have been developed using artificial intelligence to sort every postal code region in the Netherlands into one of the archetypes (Richard Westerga & Michel Emde, 2023). The 8 archetypes are:

1. Pre-1920 residences
2. Pre-war residences
3. Post-war terraced houses
4. Post-war tenements
5. Corporation residences
6. Detached houses
7. Rural area
8. Limited population & industry

The postal code regions are assigned to one of the archetypes based on their values in the following parameters: % of families with kids, energy label distribution, average household size, % of residence cooperations, distribution of rent and sale, build year, density of addresses, % gas connections, heat network, % of 3-phase grid connections.

However, not all postal code regions are similar to others in the assigned archetype. In addition to assigning regions to designated archetypes, the consortium of companies performed a goodness-of-fit analysis. This goodness-of-fit is summarized in Figure 3.6. The graph's height is the number of postal codes with a specific distance to the centroid. The centroid is a hypothetical postal code with specific values in all parameters. The goodness-of-fit can be explained as the extent to which conclusions about the provided archetype grids apply to postal code regions in the same archetype. The closer the distance of a neighbourhood to the centroid, the better the conclusions for the archetype apply to the neighbourhood.

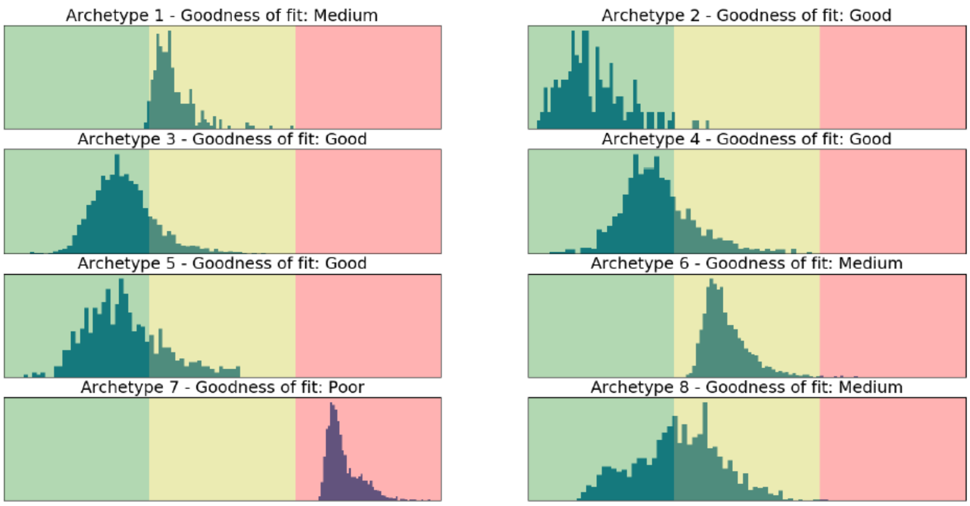


Figure 3.6: The Goodness-of-fit for the 8 GO-E Archetypes

The archetypes all have 6 example grids available in Gaia from three PGOs, 2 per PGO. These example grids are real-life grids stripped of all privacy-sensitive information which allows for drawing generalised conclusions about the grids for the neighbourhoods assigned to the archetypes. The example grids have two versions available per grid. One in the year 2023 and one in the year 2030. The grid of the year 2023 is the current grid situation of a real-world postal code of the specific archetype.

The grid of the year 2030 is based on prediction models made by the PGOs which they use for their operations. Due to non-disclosure agreements, the actual predictive models are not explained in this thesis.

For the simulation in this report, the grid of 2030 is used. The reasoning for using 2030 is based on the time frame at which infrastructural developments are made. If PTOs decide to invest in infrastructure, the installation would take years. Additionally, the grids of 2030 are more congested, and more power is drawn and supplied. Therefore, it gives a better insight into the severity of the congestion in terms of transformer load rate and the necessity of including it in decision-making.

Using SUMO, Gaia, and the GO-E archetypes, an integrated approach to decision-making can be developed. A case study is explored to investigate this connection and the influences of each system on the other. The following sections discuss the case study selection and its implementation in the different software.

3.4. Integration of SUMO and Gaia

An integrated approach to decision-making for on-route opportunity charging can only be achieved by integrating the software and thus results of the mobility and energy systems, in this case SUMO and Gaia. SUMO provides results with regards to the energy consumption and thus charging requirements of the EB service. The results of SUMO show the charging times at different capacities required to complete operation. The charging times in SUMO are between zero and two minutes. The temporal resolution of Gaia, meaning the time between events, is 15 minutes. Therefore, the increase in charging times is unable to be represented in Gaia. Only the charging capacity can be represented in Gaia.

SUMO provides Gaia with input regarding the charging capacities of the on-route opportunity chargers and as output Gaia provides SUMO with whether the capacity is available and if the EB can charge as implemented in SUMO. If that is not the case, SUMO must adapt the simulation in terms of charging duration. However, the increase or decrease in charging duration will impact the timetable, which is undesirable (Fridgen et al., 2021). Therefore, a balance must be found between charging duration (SUMO), charging capacity (Gaia) and timetable deviation (SUMO).

4

Application

The following sections describe the application of the methodology described in Chapter 3. The methodology is applied to a case study. The selection and modelling of the case study are discussed in this section. Additionally, the experimental design which will be used to gather the results found in Chapter 5 is discussed.

4.1. Case study

In the following sections, the case study for this research is selected based on a number of criteria and the corresponding characteristics of the route and the bus in the case study. Additionally, the implementation of the charging technology and method used for opportunity charging is discussed.

4.1.1. Case study criteria

To implement the methodology as described in Section 3, a single bus route will be selected to which the different charging strategies are tested. The criteria selected, and the corresponding hypotheses, are:

- The route must contain at least 10 intersections

  The minimum number of intersections relates to the impact of traffic priority on total bus consumption. The energy consumption of buses is influenced by the number of times the bus needs to decelerate and accelerate (Huan et al., 2019). 10 intersections, at a minimum, will provide enough locations where deceleration and acceleration will be omitted due to traffic priority to notice a difference in energy consumption.

- The route must contain at least 10 bus stops

  The minimum number of bus stops relates to the available potential opportunity charger locations. Locating the opportunity charger of the electric bus close to a transformer significantly reduces the costs of its installation. The costs of opportunity chargers with a capacity of >200 kW are assumed to be €250,000 (Lajunen, 2018). Prices for underground electricity infrastructure are dependent on many factors such as length, location and cable type. Installing underground infrastructure ranges in price from lower estimates of €100,000/km to €1,000,000 (Larsen, 2016) to as large as €1,500,000/km to 3,000,000/km (Benmenni, 2021). Even though direct investment costs are not considered in this study, locating opportunity chargers close to transformers is realistically preferred. The installation of underground cables can cost multiple times the cost of the charger itself. Having many potential locations for opportunity chargers reduces the costs associated with installation by reducing the expected distance to transformers and thus reducing the costs of underground cables.

- The time in between buses is at least 15 minutes

  The minimum time between buses (frequency) relates to the time discretization of the Gaia software. Gaia calculates the transformer load rate in intervals of 15 minutes. If the frequency of the buses is lower or equal to 15 minutes, there are potential overlaps and two charging events within 15 minutes could occur. This would be handled as simultaneous charging events. This would cause a doubling of the strain on the transformer even though the case study in the real world will not include double charging events.

- The route must traverse at least 3 GO-E Archetypes

  The GO-E archetypes, as described in section 3.3, are the basis of the input of Gaia. To increase the applicability of the conclusions drawn in this research, as many GO-E archetypes as possible should be included in the case study. The goodness-of-fit of the different archetypes describes the applicability of conclusions to other neighbourhoods with the same archetype classification. The goodness-of-fit of 4 archetypes are considered good. Including 3 of the 4 good archetypes is considered the minimum.

4.1.2. Case study selection

The case study selection is based on the criteria mentioned in Section 4.1.1 and the goodness-of-fit-tests in Section 3.3. Selecting a bus route to be modelled in SUMO considers the route characteristics and the goodness-of-fit of the archetypes the bus route runs. The case study selection area for this research is the city of Rotterdam. The city of Rotterdam is selected because of data availability and connections with related companies for the researcher.

Selection is done by comparing the map of Rotterdam containing the archetype distribution to the PT map of Rotterdam. Figures 4.1 & 4.2 provide the maps of Rotterdam with the GO-E archetypes, excluding medium and poor goodness-of-fit archetypes, and the PT network.

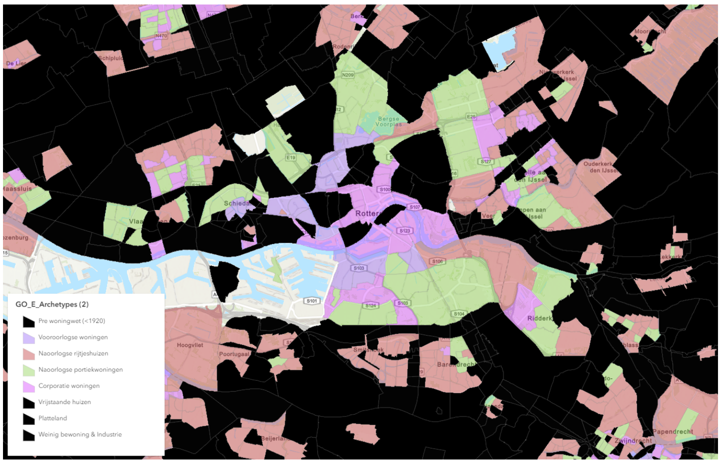


Figure 4.1: The archetype distribution of Rotterdam excluding the GO-E archetypes with a poor or medium goodness-of-fit, purple = Pre-war residences, red = Post-war terraced houses, green = Post-war tenements, pink = Corporation residences

Figure 4.2: The PT network map of Rotterdam

Apart from the city centre, few bus lines travel through only good archetypes. However, the city centre contains several intersections with various transportation options, such as trams and metros, alongside cars, buses, cyclists, and pedestrians. SUMO relies on manual input to calculate the energy consumption of buses. Manually modelling these complicated intersections would reduce the validity of conclusions due to the simplifications inherently present.

The area of Rotterdam Alexander, located in the north-east of Rotterdam, is significantly less complicated in terms of modalities at intersections and thus more accurate to model. One bus line, bus line 36, is suitable for modelling in SUMO and runs through 3 archetypes: Archetype 3 Post-war terraced houses, Archetype 4 Post-war tenements, and Archetype 5 Corporation residences. The bus line travels from the train station ”Rotterdam Alexander” to the ”Kralingse Zoom” metro station and back. Figures 4.3 & 4.4 display the bus line 36 of Rotterdam on the PT map of the RET and shown on the archetype map of Rotterdam.

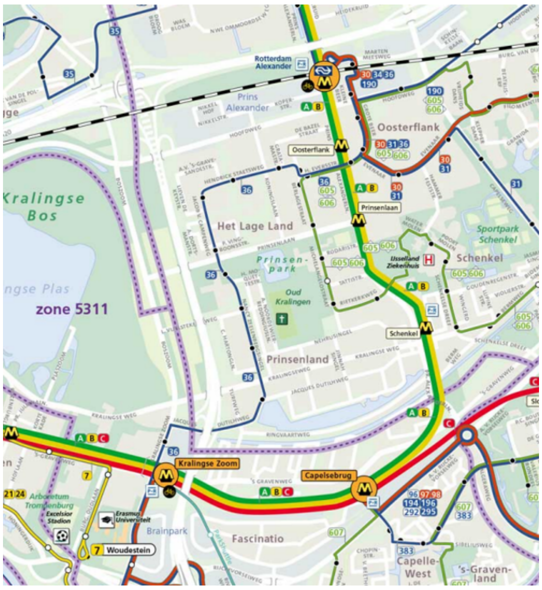


Figure 4.3: Bus line 36 in the PT map of the RET

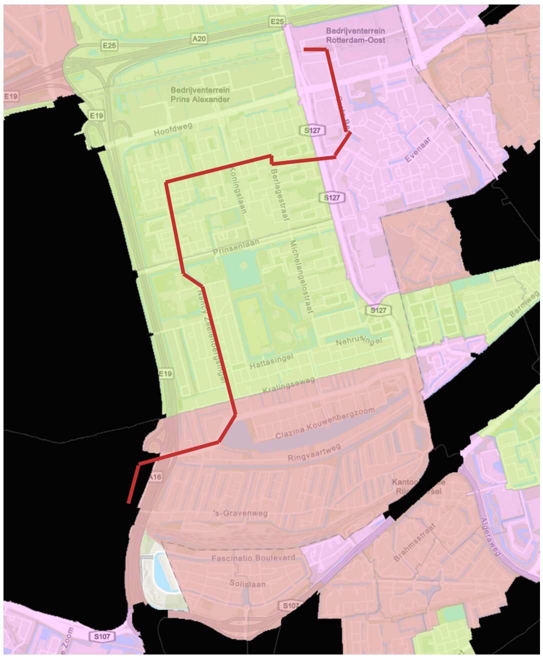


Figure 4.4: Bus line 36 shown on the archetype map of Rotterdam

Bus line 36 is a suitable case study due to its values in the following criteria:

- The route must contain at least 10 intersections. Bus line 36 has 51 intersections
- The route must contain at least 10 bus stops. Bus line 36 has 17 bus stops
- The time in between buses is at least 15 minutes. The frequency of bus line 36 is once every 30 minutes
- The route must traverse at least 3 GO-E Archetypes. Bus line 36 travels through 3 archetypes. Examples of the archetypes used in the case study can be found in Figure 4.5.

Additionally, bus line 36 does not cross complex intersections with multiple modalities, only straightforward intersections or roundabouts with bike lanes and pedestrian crossings. The bus line does cross metro lines A and B. However, the probability that a bus is hindered by this single crossing is negligible.

Figure 4.5: An example of neighbourhoods of archetype 3: post-war terraced houses (top-left), archetype 4: post-war tenements (top-right), and archetype 5: corporation residences (bottom)

Important to note that bus line 36 is characteristically not a bus line where opportunity charging would be deployed. Opportunity charging is often used for long-distance travel (approximately 25 km) where the battery must charge during operation (Estrada et al., 2022). Bus line 36 is not a long-distance route, only travelling for approximately 6 km. However, bus line 36 is suitable for this study due to the following reasons:

- This study investigates the impact of opportunity on local distribution grids. The longer-distance travel, typically associated with opportunity charging, has access to less congested distribution grids since the connections can be made outside neighbourhoods. Investigating the impact of opportunity charging on grid congestion for local distribution grids is more relevant within a city.
- Using a city bus line with stops closer to each other decreases the costs of infrastructure investments in terms of cables. As bus stops, and thus chargers, are located more closely to the transformers.
- Traffic and traffic priority are more relevant in the city centre, as long-distance bus routes often encounter substantially less traffic.
- Long-distance bus routes often travel through the rural area GO-E archetype, one of the poorest goodness-of-fit archetypes, and conclusions about grid congestion are less relevant.

Developing an integrated approach to decision-making requires understanding the current practices and characteristics of the research area. The following sections discuss the current practices of the RET, the PTO of the research area, and the input characteristics required for simulation

4.1.3. Current charging strategy of the RET

The RET, the PTO of the research area, is currently in the transition phase to full electric PT. The goal is to have a fully electric operation by 2030. 100 EBs are currently employed by the RET, accounting for 40% of the total fleet of 250 buses, and are charged using pantograph charging. The EBs are charged during the night at the ”kleiweg” depot. The additional charging is performed either at the depot or at terminal stations. Terminal stations are stations to which more than one mode of transportation or multiple bus lines are connected. Terminal stations are often bus lines' start and end stops and have longer stop times. The RET currently uses five terminal stations to charge during the day: Rotterdam Centraal, Krimpen aan den IJssel, Station Schiedam, Vlaardingen West, and Overschie (van Noortwijckstraat). The buses that do not have one of the terminal stations as one of their stops will return to the depot to charge during the day, causing deadhead trips. The RET uses pantograph chargers as displayed in Figure 4.6. The buses of the RET are supplied by manufacturer VDL.

Figure 4.6: An RET pantograph charger at the central station of Rotterdam

4.1.4. Route and bus characteristics

As input for the simulation in SUMO, two input formats are required: the route and bus characteristics. The route characteristics contain the road network's design, the lanes' speeds, priority lanes, and special lanes such as bus lanes, TRS, and bus station locations. The researcher manually inserts route characteristics into SUMO using data from Open Street Maps, Google Street View, and real-life visits. The values of the vehicle characteristics, as explained in Section 3.1, are given in Table 4.1. The values used are supplied by the bus manufacturer VDL. The EBs of VDL are used in Rotterdam by the RET. Only the recuperation efficiency is based on literature. Literature suggests a recuperation efficiency of around 15% (Ma et al., 2019).

Name	Description
Maximum battery capacity	216000 Wh
Maximum power	160000 W
Vehicle mass	15000 on average
Front surface area	8 m^2
Air drag coëfficient	0.6
Internal moment of inertia	0.01 kg
Radial drag coëfficient	0.5
Roll drag coëfficient	0.01
Constant power intake	5500 W
Propulsion efficiency	0.9
Recuperation efficiency	0.15
Stopping threshold	0.1 km/h

Table 4.1: The input values of the vehicle characteristics

Along with the route and bus characteristics, SUMO requires the addition of chargers. The technology and method of charging are required for implementation.

4.1.5. Charging technology and strategy

The charging strategy used for this research is a combination of 2 methods. Table 2.5 describes the different charging methods. This research uses two methods: Depot charging and fast terminal charging. Depot charging is considered to start the operation day with full battery capacity. Afterwards only fast charging is used at opportunity chargers to complete daily operation. For this research a starting capacity of 90% is used as travel from the depot to the starting point should be considered. Additionally, the ending capacity may not reach below 30% as the bus must safely return to the depot.

For the opportunity chargers, pantograph charging is used. This technology attaches an arm to the top of the bus which connects to a stationary pole located at the terminals. Figure 4.7 displays a pantograph charger. Pantograph chargers are used as these are most commonly used in practice (Al-Saadi et al., 2022) and used by the RET. The charging delay of pantograph charging is not significant for this research, as the deployment is often done during the braking of the bus and, therefore, near-instantaneous at the moment of standstill. Pantograph charging capacities range from 50 kW to 500 kW (He et al., 2020); for this research, both a charger of 200 kW, representative of a mid-range charger and a charger of 450 kW, the maximum capacity for the buses employed by the RET (VDL, 2023), are used. Depot charging during the day is not included in this research as this results in a substantial number of deadhead trips (Alamatsaz et al., 2022).

Figure 4.7: A pantograph charger of the RET in Rotterdam

4.1.6. Opportunity charger implementation

The implementation of opportunity chargers is twofold. First, the chargers' location must be determined. Second, the chargers' implementation in Gaia must be determined.

Charging locations are determined based on the distance to transformers and to ensure all 3 GO-E archetypes include a charger. Distance to the transformer is included due to the enormous costs associated with infrastructural investments, as explained in section 4.1.1. Even though direct investment costs are not considered in this study, locating opportunity chargers close to transformers is realistically preferred. Figure 4.8 shows the determination of the locations of opportunity chargers. For all bus stops along the route, the distance to the transformer was researched, and the bus stops located closest to transformers were chosen. Additonally, in the case of multiple bus stops with similar distances to transformers, the bus stop which interferes the least with traffic is preferred. Increasing the charging time will increase the time the EB is stationary. If this time is spent at an unfavourable location, other traffic is hindered.

The implementation of the pantograph opportunity chargers in Gaia follows a straightforward consumption pattern. The frequency of bus line 36 is once every 30 minutes. Gaia has data points for every 15 minutes. Therefore, the opportunity charger is either fully in operation with a profile value of 1 or not with a profile value of 0 and switches every 15 minutes. Figure 4.9 provides the profile of the opportunity charger for a single day (left) and week (right).

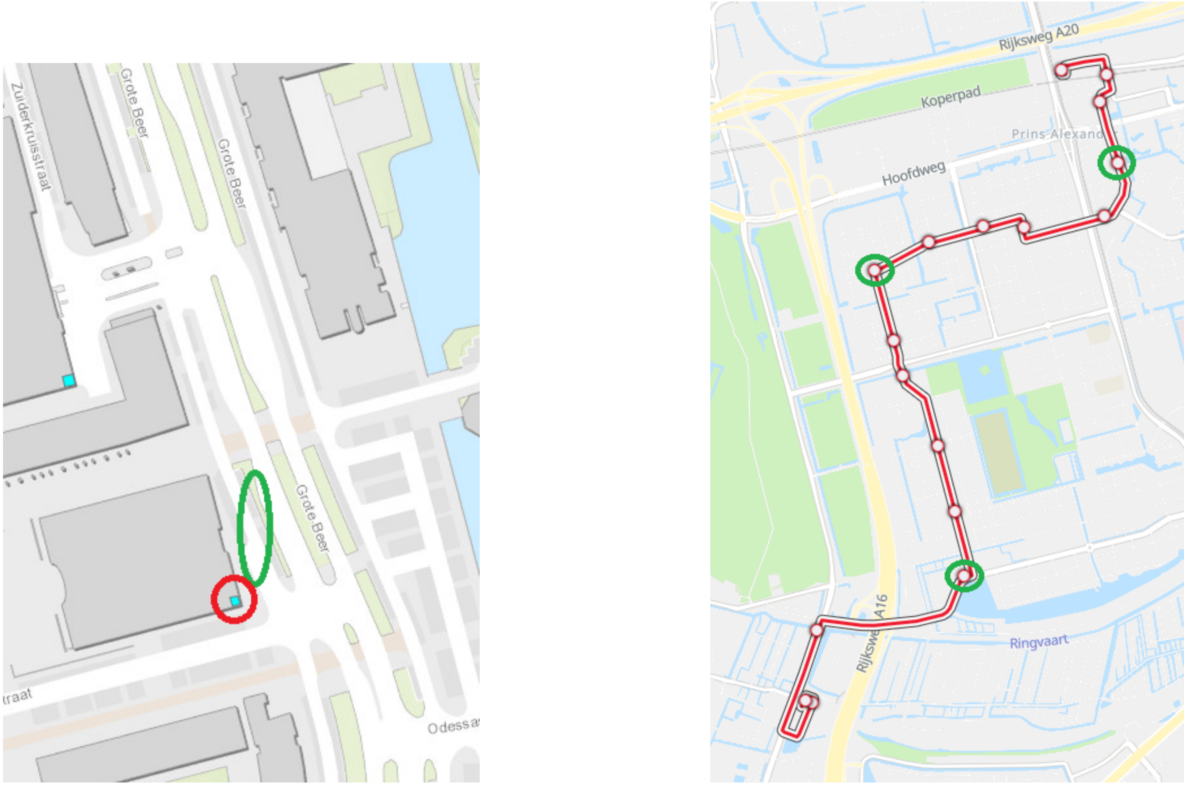


Figure 4.8: The determination of charger locations. The left picture shows the location of the transformer (red encircled) and the location of the charger (green encircled). On the right, the green circles indicate the charger locations along the route. The left picture shows the determination of the location of the upper right charging location

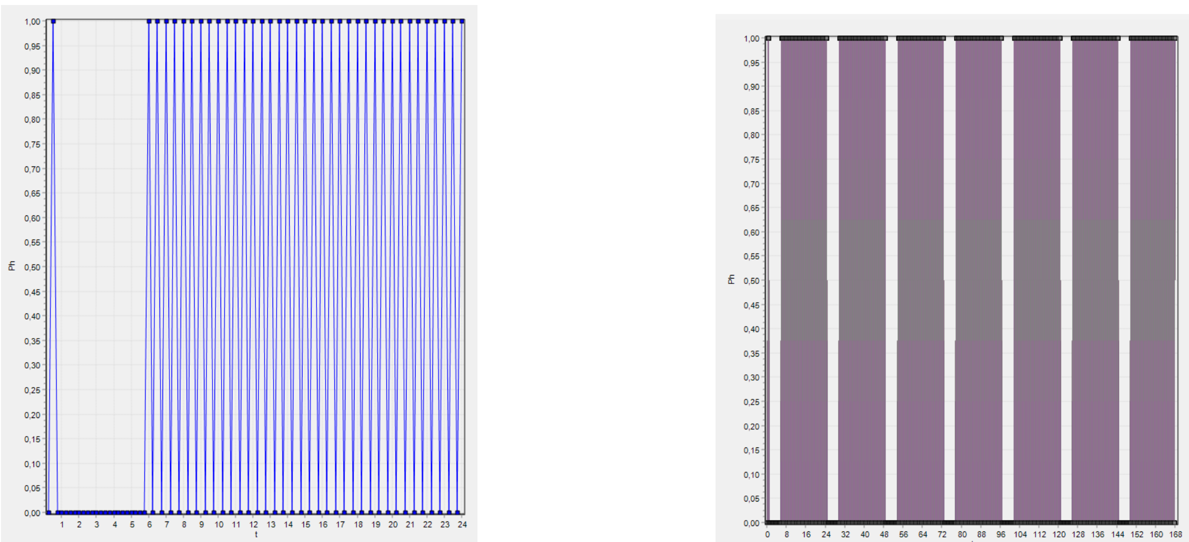


Figure 4.9: The implementation profile of the opportunity charger in Gaia for a single day (left) and a full week (right)

4.2. Experimental design

The configuration of SUMO and Gaia is complete using the information and implementation described in the sections above. To test the connection between mobility and energy systems in EB operation, different variations of the case study must be tested, which requires changing simulation variables. The next sections describe the variables and configurations that will be used to simulate the systems and gather the results described in Chapter 5.

4.2.1. Simulation variables

The operation of the bus is based on the consumption and charging behaviour of the bus. In order to test different combinations of consumption and charging behaviour, a number of strategies are developed, further explored in 4.2.2. The strategies used in this research contain a configuration of the following variables:

- Traffic intensity and priority

  Traffic has been manually inserted in the simulation. SUMO does include a random traffic module. However, this does not include road types and corresponding intensity. Logically, a major throughway road has more traffic intensity than a minor residential neighbourhood road. The addition of traffic is based on Poisson processes. SUMO does not include pure randomness but uses seeds to determine the value of the Poisson distribution. The simulations in SUMO are run 100 times to reduce the impact of the randomization seeds and determine an average and variation within the model. The value of the Poisson distribution can be changed to increase or decrease the traffic in the simulation.

  Additionally, the addition of traffic priority, as discussed in Section 3.1.1 is varied throughout strategies.

- Dwelling time

  An important aspect of the simulation is the dwelling time at the bus stops. The dwelling times have two variations: dwelling times at regular bus stops and dwelling times at bus stops with opportunity chargers. The dwelling times at regular bus stops are fixed at a single value and the dwelling times at bus stops with opportunity chargers are variable. Literature suggests dwelling times at intermediate bus stops of 10 - 30 seconds and 30 - 40 seconds at terminal bus stops (Kunith et al., 2017; Rau et al., 2019). For the simulation a dwelling time at intermediate stops of 20 seconds is used, similar to the simulation in Berlin of Rau et al., 2019. There are no terminal bus stops along the route of the case study. The dwelling time at opportunity chargers varies throughout the strategies and is a determining factor of charging capacity.

- Charging capacity

  The charging capacity of the opportunity chargers impacts the battery level of the bus and the required dwelling times to complete daily operations. The starting capacity of the chargers will be set at 200 kWh, as a starting mid-range charging option. The charging capacity can reach a maximum of 450 kWh, as determined by the manufacturer of the buses employed in Rotterdam (VDL, 2023). The capacity of the opportunity charger forms the input of the distribution grid simulation in the Gaia software.

The simulation variables allow for the construction of different strategies. Strategies use the aforementioned variables in different configurations and provide insights into the effects on the mobility and energy systems. These strategies will be tested against a set of requirements in order to determine a viable configuration of variables.

4.2.2. Strategies

To determine the required charging, the impact of the chargers on the distribution grid, and the potential influence of traffic priority on the charging schedule several strategies will be investigated. The strategies are configured using different values for the variables listed in Section 4.2.1: traffic intensity, dwelling time, and charging capacity. The strategies are configured as follows:

1. The first strategy does not interfere with the normal dwelling time of 20 seconds at the chargers. The charging capacity is 200 kW, corresponding to a mid-range fastcharger.

2. The second strategy does not interfere with the normal dwelling time, but a charger of 450 kW is used. This strategy will highlight the difference in impact that a 450 kW charger has compared to a 200 kW charger on the distribution grid.

3. The third strategy changes the dwelling time. The dwelling time will be increased until operation can be guaranteed with a 200 kW charger.

4. The fourth strategy introduces traffic priority. Traffic priority will influence the total energy requirements of the bus, as the bus will accelerate and decelerate less frequently. Additionally, a decrease in total travel time is expected. The fourth strategy does not change the dwelling time found in strategy 3.

5. The fifth strategy uses traffic priority to decrease the dwelling time according to energy requirements. The last strategy will reduce the interference with the normal scheduling as much as possible.

The evaluation of the different strategies is based on the requirements of the mobility and energy systems. Both systems have different requirements for successfully operating the bus line and the distribution grid.

4.2.3. Mobility and energy strategy requirements

The simulations of the different strategies in SUMO and Gaia are evaluated using the mobility and energy systems' requirements. Both systems are incredibly complex and have many factors influencing decision-making. However, the goals of the operators of the mobility and energy systems can be simplified to basic requirements. Specific values for the requirements are listed for the case study area.

For the mobility system, the PTO wants to satisfy demand as best as possible. For this research, it is assumed that the current timetable and route design satisfies demand. Therefore, the current design should be influenced as little as possible. This can be summarised in two requirements: the battery and its charge must be able to complete the current design (total number of trips per day) and charging should not influence the timetable to a great extent.

The mobility requirements are as follows:

1. **The bus operation should be met by the battery level of the bus**. For the case study, the following is required: The bus should be able to complete 15 round trips throughout the day, according to the RET timetable (RET, 2024). A maximum of 8640 watts of battery charge can be lost during a single trip. This is assuming the bus starts operation at 90% charge and can not go below 30% charge at the end of the day, as the bus must be able to arrive from and return to its depot. This value is obtained by dividing the maximum capacity of the bus, 216 kW, multiplied by the total difference in charge allowed, 60%, divided by the number of trips, 15. Resulting in 8640 watts, which can be lost during a single round trip.

$$\frac{216000\ W * (0.90 - 0.30)}{15} = 8640W$$

2. **The timetable should preferably be changed as little as possible**. When changing the dwelling time at charging stations the arrival times at the intermediate stops are changed. But the total travel time of the route should be changed as little as possible. For the case study, the average time, according to the timetable is 2520 seconds. The changes to the timetable are not a hard constraint as no literature was found which provides an absolute value for the maximum relative increase of the travel time for EB charging. However, Fridgen et al., 2021 do show that the extra total travel time should be kept at a minimum to retain as much utility as possible. To formulate a hard requirement which can be tested, a maximum increase in travel time of 10% is allowed.

   For the energy system, the PGO wants to provide energy in a safe and consistent manner. This means the installed infrastructure should not degrade abnormally fast and safety should be guaranteed. In order to achieve a safe and consistent grid, the transformer should not exceed 100% regularly (Mohamed et al., 2017). The energy requirement is as follows:

3. **The transformer should not exceed 100% load rate often or continuously for extended periods**. Transformers can handle greater loads than their rated capacity (>100% load rate), but exceeding this value does degrade the equipment within the transformer and cables connected to the transformer substantially more than normal operation (Mohamed et al., 2017).

The simulations in Gaia and SUMO will be run on an HP Z-book 4th generation with an Intel® Core™i7-10750H CPU @ 2.60GHz. If the computational power is deemed insufficient the TU Delft provides access to more powerful equipment. SUMO simulations are run 100 times to gain insights into the variance of the randomness in the simulations and Gaia simulations are run a single time, as the probability distributions are considered for the entire system.

5 Results

This chapter discusses the results of the SUMO and Gaia simulations run using the configurations explained in section 4.2.2.

The results for each strategy include:

- The average and standard deviation of the travel time of the bus over 100 simulation runs, used to determine the deviation of the strategy from the normal operating timetable;
- The average and standard deviation of the total energy consumed by the bus over 100 simulation runs, used to determine the charging needs of the EBs;
- The average and standard deviation of the energy regenerated using regenerative braking of the bus over 100 simulation runs, used to determine the total energy spent per round trip;
- The total energy charged by the opportunity chargers, a fixed value for every simulation, used to determine the required charging capacities;
- The average total battery loss for each round trip by the bus over 100 simulation runs, used to determine whether the configuration in the strategy allows for daily operations according to the requirements;
- The transformer load rate of the installed charger for the least impacted transformer for each archetype for a weekday and a weekend day for each month of the year. The least impacted transformer is used, as this provides an example of whether an archetype would theoretically be able to handle a charger. This decision assumes that the busstops and corresponding chargers can be relocated according to the availability of transformer capacity. Therefore, the least impacted transformer provides the highest possibility of being able to handle a charger.
- The difference in the transformer load rate between having no charger and having a 200 or 450 kW charger throughout the year. The difference in transformer load rate is used to determine whether the different archetypes are able to support a charger of the capacity in the configuration.

The SUMO simulation is shown in Figure 5.1. Only the intersections of the road are modelled, and not the entire area, as what happens after the intersection does not influence the bus but does increase computation times.

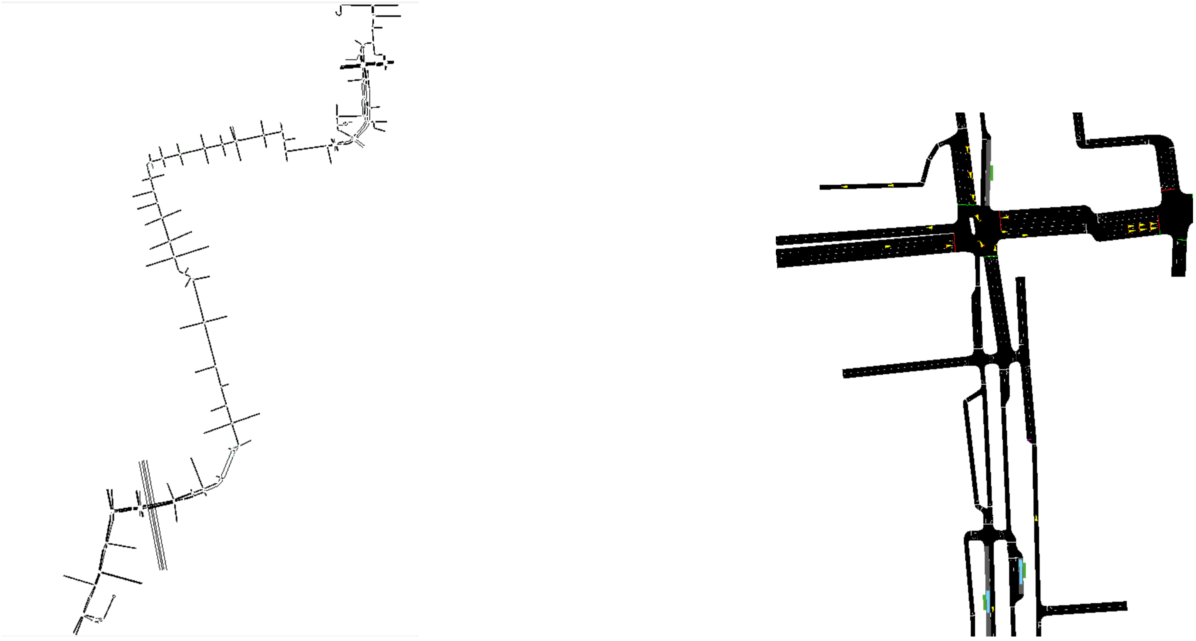


Figure 5.1: An overview and closeup of the simulation in SUMO, the EB is white and the blue bars indicate a charger

For the simulation in Gaia, the following grids and number of transformers are available and have correct data:

- Archetype 3, Post-war terraced houses: 1 grid with 5 transformer
- Archetype 4, Post-war tenements: 2 grids with in total 6 transformers
- Archetype 5, Corporation residences: 2 grids with in total 5 transformers

All grids used are of PGO Stedin, the PGO of the research area. A charger is connected to each transformer to find the least impacted transformer for each grid.

Due to data constraints, Sunday is omitted from the results, and Gaia output contains data for a generic weekday and a single weekend day (Saturday) only.

5.1. Strategy 1: 20 seconds dwelling time, 200 kW charger

The first strategy does not interrupt the dwelling time and, therefore, the operation of the bus service. The dwelling time is input as 20 seconds, as described in Section 4.2.1. The charger employed is a mid-range 200 kW charger. The results of SUMO for strategy 1 are shown in Table 5.1

	Average	**Standard deviation**
Travel time (seconds)	2502.90	64.85
Total energy consumed (Watt)	38917.42	621.80
Total energy regenerated with braking (Watt)	2228.30	64.27
Energy charged by the chargers (Watt)	6333.36	
Total battery charge lost per round trip (Watt)	30349.45	567.03

Table 5.1: The results of 100 SUMO simulation runs for strategy 1

The travel time of 2502,9 seconds on average coincides with the expectations in real life, as a round trip takes approximately 42 minutes, 2520 seconds, in real life (RET, 2024).

Given the requirements in Section 4.2.3, the bus loses more battery charge per round trip than allowed (30349.45 Watts lost, 8640 Watts allowed). The impact on the transformer is discussed in the next section. The timetable has not been impacted in any way by this strategy.

5.1.1. Impact on the grid of strategy 1

For readability purposes, the graphs of the output of Gaia are moved to Appendix A. The graphs for the entire year, shown in Figures A.2,A.3,A.4, show that the main differences in transformer load rate availability happen throughout the day and does not change substantially from month to month. However, the PV modules present in the system impact the grid in the summer months, which do not appear in the winter. Appendix A provides four graphs for each archetype to show the difference between winter and summer. One for a weekday in January, one for a weekend day in January, one for a weekday in July, and one for a weekend day in July.

The impact of the chargers will be shortly discussed per archetype.

Archetype 3: post-war terraced houses: Archetype 3's grid, shown in Figure A.5, will not be able to support a 200 kW charger in the winter months as the transformer continuously exceeds 100%. In summer, Archetype 3 could support a charger between 08:00 and 16:00. Moreover, the charger could alleviate the transformer load rate. The PV modules in the example grid increase the load on the transformer as not only demand but also supply strains the transformer. The charger would consume this excess energy before it passes through the transformer to the high-voltage grid.

Archetype 4: post-war tenements: Archetype 4's grid, shown in Figure A.6, can support a 200 kW charger except for the evening from 18:00 till 00:00 through both winter and summer. The same alleviating effect in archetype 3 can be found in archetype 4 but to a lesser extent. This can be seen from the reduction in the transformer load rate peaks.

Archetype 5: corporation residences: Archetype 5's grid, shown in Figure A.7, will be able to support a 200 kW charger throughout the day throughout the entire year. The alleviating effect found in archetypes 3 and 4 in summer is not noticeable in archetype 5.

5.1.2. Requirements evaluation of strategy 1

Table 5.2 shows the results of strategy 1 whether the requirements are satisfied or not.

Requirement	Satisfied?
The battery charge should not lose more than 8640 W	No
The timetable should not substantially be interfered with, with a maximum of 10 %	Yes
The transformer should not exceed 100% regularly or continuously	Yes

Table 5.2: The satisfaction of the case study requirements for strategy 1

The battery does not charge enough in 20 seconds at 200 kW to complete daily operation as 30349.45 Watts are lost, while a loss of 8640 Watts is allowed. To avoid influencing the timetable, the charger's capacity should be increased first. The following scenario increases the charger's capacity from 200 kW to 450 kW but does not change the dwelling time.

5.2. Strategy 2: 20 seconds dwelling time, 450 kW charger

The second strategy does not interfere with the dwelling time but employs a high-end opportunity charger of 450 kW. The charger capacity is increased to increase the total energy charged. The results of SUMO for strategy 2 are shown in Table 5.3.

	Average	Standard deviation
Travel time (seconds)	2502.90	64.85
Total energy consumed (Watt)	38917.42	621.80
Total energy regenerated with braking (Watt)	2228.30	64.27
Energy charged by the chargers (Watt)	14250	
Total battery charge lost per round trip (Watt)	22424.87	567.03

Table 5.3: The results of 100 SUMO simulation runs for strategy 2

Increasing the charger capacity from 200 to 450 kW reduces the total battery charge lost per round to 22424.87. However, this value exceeds the maximum of 8640 W. Therefore, the dwelling time must be increased.

5.2.1. Impact on the grid of strategy 2

As described in Section 5.1.1 the output graphs of Gaia are listed in the appendix. The output for the 450 kW chargers is found in Appendix B. The output of the 200 kW charger shows that there is an unnoticeably small difference in consumption patterns between week and weekend days. Therefore, the 450 kW charger output only shows a weekday in both winter (January) and summer (July). The results are shortly discussed for each archetype.

Archetype 3: post-war terraced houses: Archetype 3's grid, shown in Figure B.1, will not be able to support a 450 kW charger. The PV modules in the grid, which could assist in supporting a 200 kW charger in strategy 1, do not provide enough energy to support the 450 kW charger, even in the summer months.

Archetype 4: post-war tenements: Archetype 4's grid, shown in Figure B.2, will not be able to support a 450 kW charger. The PV modules present in the grid do not provide enough energy to support the 450 kW charger, even in the summer months.

Archetype 5: corporation residences: Archetype 5's grid, shown in Figure B.3, will be able to support a 450 kW charger from 00:00 to 18:00 in the winter and summer months. However, the evening energy demand on the grid from 18:00 to 23:59 is too high to support a charger. In this case, the summer months are slightly more favourable for the charger.

Since the grids will, in most cases, not support a 450 kW charger the following strategies will employ a 200 kW charger.

5.2.2. Requirements evaluation of strategy 2

Table 5.4 shows the results of strategy 2 whether the requirements are satisfied or not.

Requirement	Satisfied?
The battery charge should not lose more than 8640 W	No
The timetable should not substantially be interfered with, with a maximum of 10 %	Yes
The transformer should not exceed 100% regularly or continuously	No

Table 5.4: The satisfaction of the case study requirements for strategy 2

As 30349.45 Watts are lost, while a loss of 8640 Watts is allowed, the battery charge loss requirement has still not been satisfied, and more charging time is required. Additionally, a 450 kW charger does not satisfy the transformer requirement. Therefore, a 200 kW charger is used for the remaining strategies.

5.3. Strategy 3: 130 seconds dwelling time, 200 kW charger

The third strategy of this research increases the dwelling time at the chargers to such an extent that the battery charge of a round trip starts to gain. Including a 450 kW charger in the distribution grids increases the load rate substantially and should, therefore, not be preferred. For the next strategies, a 200 kW charger is used.

After increasing dwelling time by increments of 10 seconds, the first increment where the bus gains charge during a round trip is at 130 seconds of charging. This results in the SUMO output shown in Table 5.5. The negative value for battery charge lost means the battery gains charge during a round trip.

	Average	Standard deviation
Travel time (seconds)	3194.10	63.16
Total energy consumed (Watt)	40134.53	606.03
Total energy regenerated with braking (Watt)	2245.23	63.77
Energy charged by the chargers (Watt)	41166.66	
Total battery charge lost per round trip (Watt)	-3277.89	551.75

Table 5.5: The results of 100 SUMO simulation runs for strategy 3

5.3.1. Impact on the grid of strategy 3

The temporal resolution of Gaia is 15 minutes. Increasing the dwelling time by 110 seconds does not change the input and output of the simulation. The resulting impact on the grid is the same as strategy 1 found in Appendix A. This is the same for strategies 4 and 5.

5.3.2. Requirements evaluation of strategy 3

Table 5.6 shows the results of strategy 3 whether the requirements are satisfied or not.

Requirement	Satisfied?
The battery charge should not lose more than 8640 W	Yes
The timetable should not substantially be interfered with, with a maximum of 10 %	No
The transformer should not exceed 100% regularly or continuously	Yes

Table 5.6: The satisfaction of the case study requirements for strategy 3

The timetable requirement has not been satisfied as the total travel time is increased by, on average, 691 seconds, or 11.5 minutes. An increase of 27.66%. Therefore, the introduction of traffic priority is required to reduce the number of acceleration and deceleration actions. This reduces the total energy consumption which reduces the time required to charge (Huan et al., 2019). Additionally, the expected reduction in the total travel time would allow for longer charging times without disrupting the timetable.

5.4. Strategy 4: traffic priority, 130 seconds dwelling time, 200 kW charger

The fourth strategy introduces traffic priority to the SUMO simulation. To investigate the impact of traffic priority, the 130-second dwelling time of strategy 3 is used in addition to a 200 kW charger.

The SUMO output for strategy 4 is shown in Table 5.7.

	Average	Standard deviation
Travel time (seconds)	2881.43	206.72
Total energy consumed (Watt)	38320.07	699.52
Total energy regenerated with braking (Watt)	1836.80	52.25
Energy charged by the chargers (Watt)	41166.66	
Total battery charge lost per round trip (Watt)	-4685.51	672.64

Table 5.7: The results of 100 SUMO simulation runs for strategy 4

Table 5.8 compares the SUMO results of strategies 3 and 4. These strategies have the same charging schedule and capacity, but strategy 4 includes traffic priority, and scenario 3 does not.

	Average strategy 3	Average strategy 4
Travel time (seconds)	3194.10	2881.43
Total energy consumed (Watt)	40134.53	38320.07
Total energy regenerated with braking (Watt)	2245.23	1836.80
Energy charged by the chargers (Watt)	41166.66	41166.66
Total battery charge lost per round trip (Watt)	-3277.89	-4685.51

Table 5.8: A comparison of the SUMO results of strategies 3 and 4, showing the impact of traffic priority

Introducing traffic priority decreases total average travel time (-9.8 %) and increases the battery charge gained during transportation due to having a lower total energy consumption (-4.5%). The total energy consumption saved by reducing travel times and the number of accelerations and decelerations has a greater impact on the battery charge lost than the smaller gain from the reduction in energy regenerated by braking.

5.4.1. Impact on the grid of strategy 4

Due to employing a 200 kW charger in this scenario, a discussion of the results can be found in Section 5.1.1 and Appendix A.

5.4.2. Requirements evaluation of strategy 4

Table 5.9 shows the results of strategy 4 whether the requirements are satisfied or not. The total travel time with traffic priority and 130 seconds of charging is, on average, 378.53 seconds longer (15.12% increase) and can, therefore, not satisfy the timetable requirements. To satisfy the timetable requirements a reduction in charging time is required. This, in turn, increases the battery charge lost for each round trip. The battery charge lost per round trip can be increased by 13,325.51 Watts, as 8640 Watt loss is accepted and 4685.51 Watts are gained now, and still satisfy the requirements. Therefore, the charging time of strategy 5 is reduced to satisfy the timetable requirement while continuing to meet the battery charge requirement.

Requirement	Satisfied?
The battery charge should not lose more than 8640 W	Yes
The timetable should not substantially be interfered with, with a maximum of 10 %	No
The transformer should not exceed 100% regularly or continuously	Yes

Table 5.9: The satisfaction of the case study requirements for strategy 4

5.5. Strategy 5: traffic priority, variable dwelling time, 200 kW charger

The fifth strategy uses the introduced traffic priority of strategy 4 to decrease the time spent at the chargers by decreasing the total energy spent. The dwelling time is reduced until the battery charge requirement can not be satisfied. The last value of dwelling time that satisfies the requirement is a dwelling time of 90 seconds. The resulting SUMO values are listed in Table 5.10.

	Average	Standard deviation
Travel time (seconds)	2634.98	59.42
Total energy consumed (Watt)	37888.30	544.67
Total energy regenerated with braking (Watt)	1857.37	53.63
Energy charged by the chargers (Watt)	28500	
Total battery charge lost per round trip (Watt)	7528.29	506.05

Table 5.10: The results of 100 SUMO simulation runs for strategy 5

5.5.1. Impact on the grid of strategy 5

Due to employing a 200 kW charger in this scenario, a discussion of the results can be found in Section 5.1.1 and Appendix A.

5.5.2. Requirements evaluation of strategy 5

Table 5.11 shows the results of strategy 5 whether the requirements are satisfied or not. The reduction of the charging time has reduced the total travel time to 2635 seconds. This is an increase of 132.1 seconds (5.3%) when compared to the baseline situation. This satisfies the timetable requirement.

Requirement	Satisfied?
The battery charge should not lose more than 8640 W	Yes
The timetable should not substantially be interfered with, with a maximum of 10 %	Yes
The transformer should not exceed 100% regularly or continuously	Yes

Table 5.11: The satisfaction of the case study requirements for strategy 5

Introducing traffic priority thus allows for the extension of charging times without interrupting the timetable for more than 10% and while using a mid-range charger of 200 kW. The extension of charging times is increased to such an extent that daily operation can be accomplished while relying solely on charging during the on- and offboarding for the extra charge during the day. Given that the bus charges to full during the night.

5.6. Strategy requirement satisfaction summary

The previous sections describe different strategies regarding dwelling time, charging capacity, and the inclusion of traffic priority. The requirements of the mobility and energy systems have shown that a synergy between the two systems is required to run a bus service that considers both systems.

The results of the SUMO simulations are summarised in Table 5.12. The values indicated in red show the values which do not satisfy the requirements.

Strategy	**1**	**2**	**3**	**4**	**5**
Charger capacity	200 kW	450 kW	200 kW	200 kW	200 kW
Dwelling time	20 sec	20 sec	130 sec	130 sec	90 sec
Traffic priority	No	No	No	Yes	Yes
Travel time (seconds)	2502,90	2502,90	3194,10	2881,43	2634,98
Total energy consumed (Watt)	38917,42	38917,42	40134,53	38320,07	37888,30
Total energy regenerated with braking (Watt)	2228,30	2228,30	2245,23	1836,80	1857,37
Energy charged by the chargers (Watt)	6333,36	14250	41166,66	41166,66	28500
Total battery charge lost per round trip (Watt)	30349,45	22424,87	-3277,89	-4685,51	7528,29

Table 5.12: The average results of 100 runs of the different strategies in SUMO

The results of the full requirement evaluations of the different strategies are listed in Table 5.13.

Strategy 1 is unable to satisfy the battery charge requirement as more charge is lost than allowed to perform a full day of operation.

Strategy 2 follows strategy 1 by aiming to decrease the energy charge lost by increasing the charging capacity from 200 to 450 kW. However, this did not satisfy the battery requirement. Additionally, the impact on the grid increased to such an extent that in most cases, the transformer exceeded 100%, as explained in Section 5.3.

Strategy 3 follows strategy 2 by decreasing the charging capacity of the charger to satisfy the transformer requirement. To satisfy the battery charge requirement the dwelling time, and thus charging time, was increased. This strategy managed to satisfy both the battery charge and transformer requirements but deviated too much from the timetable to satisfy the timetable constraint.

Strategy 4 follows strategy 3 by introducing traffic priority. The aim of traffic priority is to reduce energy consumption by reducing the amount of acceleration and deceleration actions and decreasing total travel time by having priority in traffic. Traffic priority does reduce the aforementioned energy consumption (-4.5%) and travel time (-9.8%), but not to such an extent that all requirements were satisfied. Strategy 4 ends every round trip with a gain in battery charge. As the battery charge is allowed to reduce by 8640 W, a new strategy is used to satisfy the timetable constraint.

Strategy 5 follows strategy 4 by decreasing the dwelling time to the minimum value where the battery charge requirement is satisfied. This results in a dwelling time of 90 seconds. Thanks to the use of traffic priority, the total travel time of strategy 5 is only 5.3% higher on average than the baseline situation and, therefore, satisfies all constraints.

Strategy	**1**	**2**	**3**	**4**	**5**
Charger capacity	200 kW	450 kW	200 kW	200 kW	200 kW
Dwelling time	20 sec	20 sec	130 sec	130 sec	90 sec
Traffic priority	No	No	No	Yes	Yes
Requirement	**Satisfied?**				
The battery charge should not lose more than 8640 W	No	No	Yes	Yes	Yes
The timetable should not substantially be interfered with, with a maximum increase of 10%	Yes	Yes	No	No	Yes
The transformer should not exceed 100% regularly or continuously	Yes	No	Yes	Yes	Yes

Table 5.13: The satisfaction of the requirements of the mobility and energy systems by all strategies

5.7. Traffic intensity analysis

The strategies in the previous sections vary the values of dwelling time, charging capacity and traffic priority as described in Section 4.2.1. However, an important aspect of the traffic simulation is traffic intensity. Traffic intensity means, in this case, the number of (other) vehicles on the road, when compared to the original traffic conditions. The simulations in SUMO describe only a single round trip. Traffic intensity changes throughout the day. To capture the possible influence of traffic on energy consumption, and therefore charging needs of the bus, during the day a traffic intensity analysis is performed.

The traffic intensity analysis analyses the effects of traffic intensity on travel time, energy consumption, regenerative braking and total battery charge lost of the EB. For this analysis, the traffic intensity factor ranges from 0.5 to 1.5 (50% to 150% of original traffic). The original traffic is manually included in the simulation and is based on total travel time, which is within a minute of the travel time according to the RET, as seen in strategy 1. Additionally, the dwelling time is 20 seconds and the charging capacity is 200 kW. The reason to not increase the dwelling time is to capture as much of the normal operating conditions as possible.

The analysis provides an answer to whether the energy requirements and, thus, charging requirements of the buses are widely varying with traffic intensity or not. This increases the applicability of the results found in the previous sections. As the charging times do not need to change if traffic changes.

Figures 5.2, 5.3, 5.4, and 5.5 provide the sensitivities of both the averages and standard deviations of travel time, total energy consumed, total energy regenerated with braking, and the total battery charge lost per round trip of the bus, respectively.

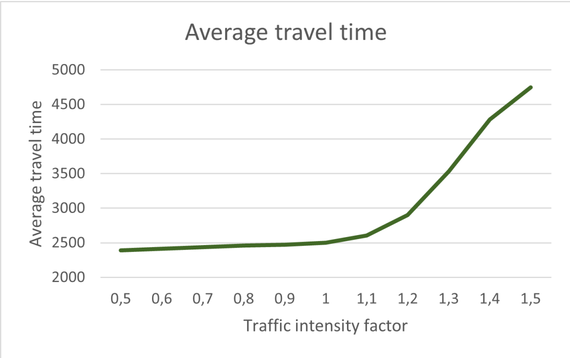
The results show that travel time increases with an increase in traffic. This can be attributed to the congestion on the road in the simulation. The simulation suggests that the infrastructure is able to handle traffic increases up to a specific value, after which total travel time increases drastically. Additionally, travel time becomes more volatile with a substantially increasing standard deviation when traffic increases. This can be attributed to the congestion at different times and locations throughout the bus's round trip.

The total energy consumed increases in both directions when increasing and decreasing the traffic. The increase in consumption in lower traffic conditions might be attributed to the fact that the acceleration and deceleration actions are steeper. With less traffic, the bus can accelerate more, consuming more power, but also decelerate faster and more, as seen in the regenerative braking graph. The increase in total energy consumption with more traffic can be attributed to increased travel time, increasing the impact of auxiliaries such as air conditioning and payment systems. Regenerative braking indicates that with higher traffic intensities the braking regenerates less and, thus, suggests lower acceleration and deceleration costs.

The total battery charge lost follows a similar path to the total energy consumed. However, at 1,2 and 1,3 intensities, the battery charge loss drops. This can be attributed to a small number of simulation runs where the bus can not re-enter traffic due to congestion. But this waiting happens to be at its charging station at a small number of simulations. This drastically decreases the battery charge lost for that specific run, thus decreasing the average. This is echoed by the increase in standard deviation.

It is important to note that in total energy consumed, regenerative braking, and total battery charge lost, the differences stay below 10% of the baseline situation (intensity factor 1.0). However, total travel time increases by nearly 100%. This suggests that consumption is not closely related to total travel time.

The literature often describes the energy consumption as kW per kilometre, and not per second. This analysis provides an example of this claim in terms of energy consumption not changing substantially with traffic intensity and an increase in travel times. However, no tests on further distances and energy consumption were performed.



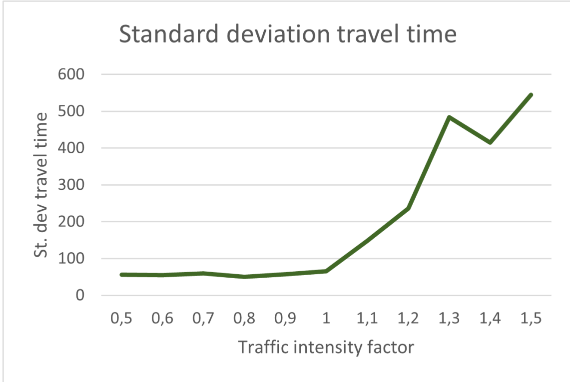
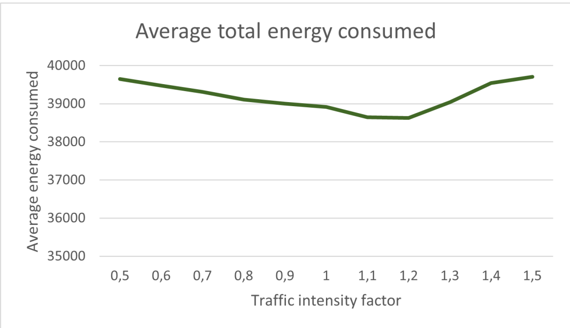


Figure 5.2: The average and standard deviation of total travel time under different traffic intensities



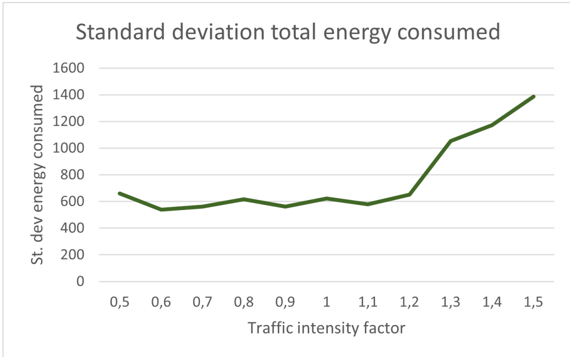
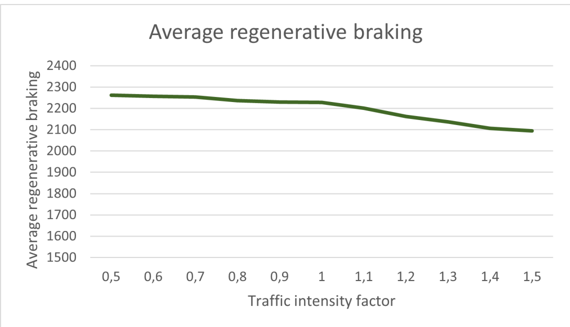


Figure 5.3: The average and standard deviation of total energy consumed under different traffic intensities



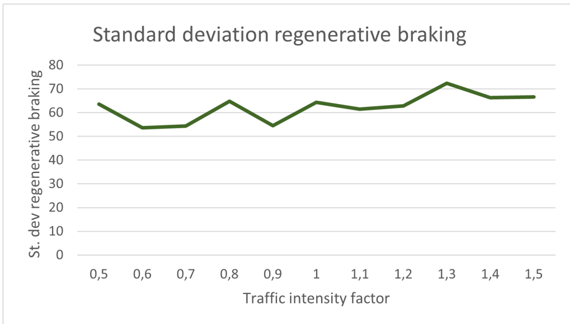
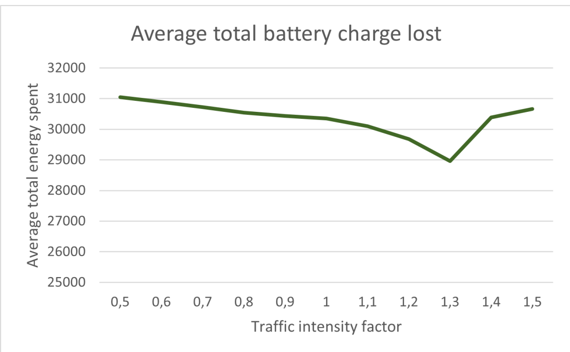


Figure 5.4: The average and standard deviation of total energy regenerated with braking under different traffic intensities



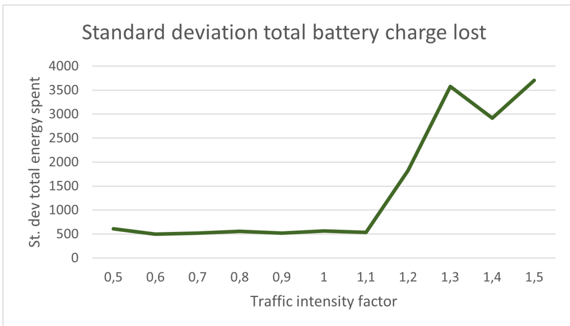


Figure 5.5: The average and standard deviation of total battery charge lost per round trip under different traffic intensities

6
Discussion

In this chapter, the most important results of this research are discussed. The discussion is structured in three parts: first, the results are discussed; second, the methodology is discussed; and third, the scientific and societal contributions are discussed.

6.1. Results discussion

The results shown in Section 5 provide an example of an integrated approach to decision-making, including both the mobility and energy systems, through the use of two different simulation software: SUMO and Gaia. The simulation environments were applied to the case study of bus line 36 in Rotterdam. Results are obtained using five strategies explained in Section 4.2.2. The aim of the different strategies is to show the necessity of including mobility and energy systems in the design of a charging strategy.

The results, including those of the SUMO and Gaia simulations, will be discussed separately. After this, the requirement evaluation will be discussed.

6.1.1. SUMO results discussion

The results of SUMO include values for the total travel time, the total energy consumed, the total energy regenerated with braking, the energy charged by the opportunity chargers and the total battery charge lost per round trip for the EB.

Strategy 1 in Section 5.1 shows similar travel times to real life using dwelling times found in the literature with an average of 2502,90 seconds travel time in SUMO compared to a listed travel time of 2520 seconds in real life (RET, 2024).

To check whether the total energy consumption aligns with the literature, it must be divided into its components and whether they coincide with reality. The total energy consumed consists of two major components: driving and constant power usage. The average consumption of EBs ranges from 1.24 to 2.48 kW per kilometre, based on numerous literature sources (Gao et al., 2017). The bus route of line 36 is 12 kilometres long for a round trip. Constant power intake is input as 5500 Watts, as supplied by the RET. The constant power intake supplies, for example, the airconditioning, lights and payment systems. The parameter value is the consumption for every 15 minutes. Multiplying the constant power intake with the route duration results in a constant power intake of 15400 Watts. Removing this from the total average energy consumption of 38917.42 Watts leaves 23517.42 Watts. Dividing by the route length of 12 kilometres results in a consumption of energy for driving of 1.96 kW per kilometre. In addition to the range provided by Gao et al., 2017, Estrada et al., 2022 determine a driving cost of 1.9 kW per kilometre. Driving consumption is, therefore, in line with the literature.

The total energy regenerated with braking multiplies the recuperation efficiency and the total power exerted during braking. The current regenerative braking values recover only 5.73% of the total energy consumed. Little research has been done on the total effect that regenerative braking can have on the total energy expenditure of buses. A single paper, by Perrotta et al., 2012, is identified which values regenerative braking as a percentage of total expenditure for EBs. This value of 21% does not coincide with the value found in this research, 5.73%. The value taken for the recuperation efficiency in the case of Perrotta et al., 2012 is 60% in its worst case for the given supplier. The recuperation efficiency of this research is only 15%. If we were to value this at 60 %, the total regenerative braking would represent 4 times its current value at 22.92%. This value is much closer to the value found in literature. This suggests that the implementation of regenerative braking is correct, only the value chosen in this research is conservative.

The energy charged by the chargers is simply a multiplication of their capacity, efficiency, and time spent at the chargers. The supplier of the EBs of Rotterdam supplied the capacity and efficiency, so the values coincide with those in real life.

The standard deviations of the results do not change substantially from strategy to strategy. Only a single strategy, strategy 4, has substantially different standard deviations. These standard deviations are caused by a single run, with randomization seed 36, where the bus cannot continue its journey due to an intersection coming to a deadlock, a situation where traffic from all entrances of the intersection crosses each other and no one can give right of way to one another. SUMO handles this by assessing the situation and teleporting vehicles from the deadlock. However, this specific deadlock happens multiple times after each vehicle is teleported. The exact reason for this happening was not found. The deadlock intersection increases the total travel time of said randomization seed to 4841 seconds and its energy consumption to 42424.60 Watts. Both are substantially higher than the average. The impact on the averages is negligible due to having 100 runs, but this seed explains the increase in standard deviations for strategy 4.

A large aspect of traffic priority not explored in this thesis is the effect of traffic priority for buses on the other users of the traffic network. Many users will be negatively affected in terms of travel time and fuel expenditure due to the priority of the bus. While this is an important aspect to consider when developing charging strategies, this thesis aimed to provide insight into the possibilities of enabling opportunity charging with traffic priority. The potential benefits and costs have not been fully explored. Suggestions for further research can be found in Section 7.1.

6.1.2. Gaia results discussion

The results of Gaia are visualised in both graphs for a full year and graphs for single days. The graphs for the full year, where every month has a representative weekday and weekend day, show that differences in consumption patterns and the impact of PV modules throughout the year are present in the grids. However, the differences from month to month are substantially smaller than the differences within a day. Therefore, the results used for the requirements evaluation used 4 graphs representing single days. One for a weekday in January, one for a weekend day in January, one for a weekday in July and one for a weekend day in July. This method of visualising the results was chosen to emphasise the differences between winter and summer. The differences between winter and summer were clearly shown, even showing that the charger can have an alleviating effect on the transformer when too much power is gained from PV modules present in the grid, which is then used by the charger before the excess energy enters the high-voltage grid.

However, this results in conclusions only being drawn about the most extreme consumption month, January, and the most extreme PV production month, July. The months in between are not specifically covered, and therefore, the conclusions drawn about the possibility of using 200 kW or 450 kW are generalised for winter and summer.

One major interesting finding is the unnoticeable difference between weekdays and weekend days. The differences in transformer load rate between weekdays and weekend days do not exceed more than 3%. The papers identified in Chapter 2 often do not distinguish between days of the week but merely between representative days throughout the year. The results from Gaia in this thesis support this strategy not to include differences between weekdays and weekend days.

The difference between a 200 kW charger and a 450 kW charger on the grid is that the peaks are 2.5 times higher. This suggests there is a linear correlation between the charging capacity of the opportunity charger and the load rate on the transformer.

A difference between the methodology and the results is the omission of Sundays from the results. Sundays were removed from the results due to a lack of consistent data. Some grids included data for Sundays, others included only hourly data for Sundays, and some did not include any data on Sundays. Therefore, the decision was made to exclude Sundays from the results. However, the practice of only including a single workday and a single weekend day is common practice for PGOs, which provides an answer to the existence of incomplete data for Sundays. As Sundays are often not used in real life simulation.

Additionally, the methodology mentions 6 grids for each archetype. These 6 grids are comprised of 3 different suppliers, including the PGO of the research area. The decision to only include the grid data of the PGO in the research area was made since including all 6 grids increased the number of results and computation times. The larger number of results and graphs did not drastically change the outcomes and made the conclusions more unclear.

6.1.3. Requirements evaluation discussion

As part of the results, requirements for the mobility and energy systems are evaluated. The requirements simplify the intricacies that affect the mobility and energy systems. However, the main goals of the different systems can also be simplified. First, the PTO wants to achieve a timetable that includes charging, which satisfies demand; in this case, it is assumed that the current timetable satisfies this demand. This requires the battery to stay at an acceptable level of charge and the current timetable to not be influenced greatly. Second, the energy provider of the area does not want the opportunity charger to degrade the installed infrastructure and decrease the safety of the distribution grid.

To capture the requirements of the PTO and the energy provider, the requirements are formulated using specified values for certain output parameters, in this case the travel time and battery charge lost per round trip. Using the requirements, one can state that keeping the mobility system as is and changing only the energy side by increasing the charger capacity does not satisfy all requirements. Moreover, changing only the mobility side by increasing charging times does not satisfy all requirements as this impacts the timetable greatly. Taking the mobility and energy systems into account simultaneously is required to satisfy all requirements.

The simplification of the system removes a large part of the intricacies of the mobility and energy systems but does provide an example of the necessity to consider both in the decision-making of EB planning.

6.2. Method discussion

This research provides an example of an integrated approach to decision-making in bus service design; for this, two different simulation methods are required to evaluate the impact of the strategies on both the mobility system and the energy system. The simulation software of SUMO, explained in Section 3.1, is used for the mobility system. The simulation software of Gaia, explained in Section 3.2, is used for the energy system.

An integrated approach can be developed using a combination of different methods. In the literature, two main methods of mobility service design are found: optimization and simulation. The reason optimization is not included in this research is due to the goals of this research. This research attempts to investigate the impact that opportunity charging has on bus service design and the distribution grid by including different charging times, capacities and the inclusion of traffic priority. Optimization models provide the optimal solution to a given model under specific constraints. However, changing minor aspects of the model could result in drastically different optimalities and substantially impact, for example, the energy consumption of the buses. Optimality is not the goal of this research. The goal is to investigate the effects of minor changes to existing operations. Therefore, simulation is used as a method for both mobility and energy systems. The results of this research can be used in an optimality model as further explained in Section 7.1. The next sections further explore the decision to use SUMO and Gaia.

6.2.1. SUMO methods discussion

SUMO is the open-source traffic simulation software (TSS) used in this research as explained in Section 3.1. The input of SUMO has been gathered from multiple sources; the RET, experts and Open Street Maps. SUMO shows as output the potential impact of traffic regulations and the behaviour and interactions of vehicles under said regulations.

Many TSS are available with many applications (Ejercito et al., 2017; Ullah et al., 2021). SUMO is highly customizable and can be configured for any situation. Additionally, an electric vehicle module is already present in the software (Kurczveil et al., 2014). Moreover, the researcher has availability to experienced users for SUMO and little expertise for other TSS. The customizability, relevance and available expertise led to the decision that SUMO is most suitable.

However, the customizability introduces potential simulation errors and variance in its construction. The SUMO simulation model is based on mostly manual input. Manual input was required for the following simulation aspects: the road network and layout, the intersections, the traffic regulation systems (TRS), the vehicle parameters, and the traffic. Each of these manual inputs has its own potential for errors.

First, the road network and layout were manually input using data from Open Street Maps. The length of roads was measured and recreated in SUMO. SUMO does include an Open Street Maps import tool. However, the research area was too large for the import tool to work correctly. The measuring and recreation of the roads were done as meticulously as possible, but using the import tool would reduce uncertainties.

Second, the intersections and related TRS were manually designed. The layout of the intersections was recreated from Google Street View and checked by the researcher in real life. The TRS in Rotterdam operates using articulated lanes, where oncoming vehicles are registered, and the traffic lights are configured to respond to oncoming traffic. SUMO does include a TRS configuration using articulated lanes. However, the researcher could not implement an articulated TRS where only the EB would have priority. Therefore, the decision was made to reduce the complexity of the TRS and use timed cycles. These timed cycles allow for the introduction of priority for the lanes on which the bus drives by increasing green time. Traffic priority was therefore included in intersections with a TRS, but it is not an accurate depiction of the case study. Other areas do use timed cycles.

Third, the vehicle parameters for the EB were manually input as described in Section 3.1. The customizability of vehicle parameters allows for the input of any chosen vehicle. However, this does introduce errors when the values do not correspond to real life. As seen in Section 6.1.1 values for the recuperation efficiency can be drastically different. This can reduce the applicability of this research to other research areas with different parameters.

Last, the traffic was manually input in the SUMO simulation. The input process meant selecting every ingoing lane from each intersection and providing traffic parameters to other outgoing lanes of each intersection. This act was done as meticulously as possible and took road types, such as deadends and throughways, into account. Traffic probability values were then increased until a similar travel time to real life was achieved. As traffic is a highly dynamic system, a manual representation does not do justice to all intricacies. However, due to traffic itself not being an interest in this research but only its effect on the bus, the reduction in validity of traffic movements is not severe for the goal of this research. Moreover, other modalities, such as pedestrians and cyclists, were not included in the simulation. Due to time constraints, these other modalities were not considered. However, for the goal of this research, the total travel time is of the greatest importance in showing the potential benefits of traffic priority. Whether crossing traffic is cars or pedestrians does not substantially impact the results as long as the total travel time reflects real life.

6.2.2. Gaia methods discussion

Gaia is the software used to investigate the effects of opportunity charging on the low-voltage distribution grid. Besides implementing the opportunity charger, the researcher did not change Gaia's configuration or calculation methods. Gaia is the only software of its kind available to the author. More mid-to-low-voltage grid design software can be found. However, these are either behind a substantial paywall or confined to company use only. Gaia was provided as a tool by the companies affiliated with the researcher. Moreover, Gaia is the software currently used by the most relevant PGOs in the Netherlands, including Stedin. This vouches for its accuracy and validity.

A single other publicly available software was identified that would provide similar results, OpenDSS, as used by Elnozahy and Salama, 2014. However, the data available from the energy providers was incompatible, so OpenDSS was not considered further.

Gaia is fully dependent on the quality of the input the user provides. As seen in the results and the discussion of the results of Gaia, the input data was, at times, incomplete or inconsistent. However, the incomplete and inconsistent data was filtered out and did not influence the results shown in this research. The input of Gaia consists of GO-E archetype data, discussed in the following section.

6.2.3. GO-E Archetypes discussion

The research presented in this thesis uses the GO-E archetypes, described in Section 3.3, to provide results and conclusions based on real-life data. However, due to the privacy restrictions of the grid data, it is unclear to what extent the results shown actually coincide with the case study. The goodness-of-fit tests provide arguments to assume that the results for the archetypes coincide with the case study, but are no guarantee.

However, the inclusion of GO-E archetypes does allow for the wider application of the results found in this research to other neighbourhoods in the Netherlands. Archetypes 3, 4, and 5 all have good results in the goodness-of-fit test, and therefore, the results can be assumed to be very similar for other neighbourhoods in the same archetype. Additionally, the inclusion of GO-E archetypes increases the reproducibility of this research. The reproducibility is increased because the results regarding the grid are not case-study specific but can be applied and reproduced for all grids in the archetype.

The grid data used in this research is based on PGOs' prediction models. Prediction models of energy consumption behaviour are notoriously difficult to estimate, which is why the grids are so congested, as infrastructure installation is based on predicted demand. However, for this research, using prediction models by the energy suppliers is as close to reality as reasonably possible.

6.3. Scientific and societal contribution discussion

This research's scientific and societal contribution is found in integrating mobility and energy systems. As mentioned in Chapter 2, the design of EB routes and schedules is often approached by either the mobility or the energy system. Both in research and in practice. The failed implementation examples mentioned in Chapter 1 show that an integrated approach is not being used in practice, and therefore, the implementations fail to provide a bus service that can satisfy demand.

In the case of failed implementation, one of the two systems is often simplified. Either the energy system is simplified when designing from a mobility point of view, or the mobility system is simplified from an energy point of view. When simplifying the energy system, it is often assumed that capacity is readily available and chargers can provide their full rated capacity at every moment in time. This research clearly shows that, in the case of installing chargers in residential neighbourhoods, capacity is not available at all times throughout the year or the day, and it shows that the timing of charging should be carefully considered. When simplifying the mobility system, it is often assumed that bus services run on time and that charging during the day is unnecessary to complete daily operations. This research clearly shows that reducing the charging time drastically impacts the ability to complete daily operations and, when not considered carefully, could bring an EBF to a standstill.

EB services are necessary to satisfy mobility needs in future urban areas. This research shows that an integrated approach must be used to satisfy all mobility and energy system requirements and guarantee successful implementation. Additionally, it provides an example of how influencing one system, the mobility system, can influence and enable the other system, the energy system. The successful implementation of EBFs is required to ensure that urban regions of the future can satisfy mobility demand.

Moreover, the analysis of the influence of traffic intensity on bus energy consumption shows that the assumption that energy consumption is mainly based on total travel distance, which is often suggested in the literature, can be verified. Therefore, the assumptions made in multiple papers that energy consumption can be simplified into a single value for energy spent per kilometre are agreed upon in this research.

Additionally, using GO-E archetypes is an example of using protected data to provide results and draw conclusions based on real data. These results and conclusions can be used in other case studies within the same archetypes in the Netherlands.

The main conclusions found in this research are discussed in the next Section.

7 Conclusion

This research has shown that an integrated approach, including both mobility and energy dynamics, is key in assessing design decisions regarding EB operations in urban areas. EBs are important in achieving global emission goals and satisfying urban mobility demand. The implementation of EBs requires careful design and planning. In the design and planning of EBFs, the mobility and energy systems must work in parallel to satisfy the demand for mobility and electricity for the EBs while retaining a functioning electricity distribution grid. The PTOs want to operate a service that satisfies mobility demand, and PGOs want to operate a safe and consistent grid. In current design processes, the mobility and energy systems are often separately accounted for, causing implementation failures (NOS, 2023; Omroep Flevoland, 2023; OVPro, 2023).

Current implementations of EB charging rely heavily on depot charging. Depot charging fully charges the buses at night, which is preferred in terms of costs and grid availability. However, current battery capacities and efficiencies do not allow for full days of operation on a single full charge. Additional charging during the day is required. Depot charging is also used during the day, which means buses stop service and return to the depot. This results in a substantial number of deadhead trips, which are trips without passengers, reducing the operation time of each bus and wasting energy. Additionally, the collective charging at a single depot during the day strains the local grid to such an extent that voltage fluctuations appear and a safe and consistent energy supply can not be guaranteed.

A potential solution to charging the EBs during the day is opportunity charging. As used in this thesis, opportunity charging describes installing chargers at bus stops where EBs are charged during passengers' on- and offboarding at high capacities. This solution disperses the energy demand peaks of the EB charging throughout the city and, thus, to different connections to the high-voltage grids via different transformers. Eliminating the need for multiple chargers connected to a single transformer and reducing the impact on the operation time of the EBs.

The EB scheduling should take the charging of the buses at bus stops into account. Additionally, to use the chargers at high capacity, the integration of the chargers in the local distribution grid should be considered.

This thesis considers both the mobility system, EB scheduling, and energy system, transformer load rate, to implement opportunity charging to satisfy the charging requirements of EBs that are not met with depot charging alone. The research is performed on a case study in the city of Rotterdam in the Netherlands.

The following questions have been answered throughout this thesis.

SQ 1: What are the current charging strategies for electrical bus fleets:

Current charging strategies use depot charging as their main method of charging. In most cases, depot charging is used for both charging at night and additional charging throughout the day. Depot charging throughout the day causes many deadhead trips, trips without passengers and revenue, and reduces the effective operating time of each EB. Depot charging is often done using two different methods. During the night, low-capacity plug-in chargers are used. During the day, high-capacity plug-in chargers are used.

Recently, chargers at terminal stations at the end of bus routes have seen their introduction. High-capacity pantograph chargers are used for terminal station charging. However, in practice, the charging times at terminal stations are often shortened due to delays along the bus route but continuing the schedule as planned. This results in buses being unable to complete daily operations due to a lack of charge.

The literature suggests charging at intermediate stops during passenger on- and offboarding as a potential solution to the additional charging throughout the day. However, this strategy has remained in theory and is not seen in practice.

Other charging strategies include continuous contact line or inductive charging during operation or battery swapping. With battery swapping, the same issues of depot charging arise, which causes many deadhead trips. However, battery swapping has the advantage that there is no actual charging time during the bus operation as the battery can be swapped for a full battery.

Charging strategies are almost exclusively developed using only the mobility system as a deciding factor. Many optimization models have been developed, but they fail to represent the energy system fully. The energy system is often simplified by assumptions that a decrease in total charging costs is directly related to a decrease in impact on the grid.

SQ 2: How is grid congestion considered in current charging strategies:

The energy system and its demand and supply, or grid congestion, are often disregarded or simplified within optimisation models and charging strategies. Grid congestion and availability are included in optimization models in one of two ways; first, the model uses a fluctuating energy price to determine the total charging costs. The charging costs are assumed to be directly correlated with the impact on the grid. However, this has been disproven in literature. Second, the model uses grid availability to remove charging locations from the potential locations. However, this does not include any fluctuations in demand and supply throughout the day.

The literature provides a few examples of research into the impact of EB charging on local grid congestion. However, this is limited to terminal charging and combines multiple chargers at a single location. Additionally, the models use fictional data to determine the load rate on the transformer and fail to capture the dynamics of energy demand and supply.

Recent news shows the failure to accurately represent grid congestion in EB implementation. Charging times are undervalued in timetables, and charging capacities are not consistently present.

SQ 3: To what extent does opportunity charging impact local grid congestion?:

Opportunity charging, as used in this research, substantially impacts grid congestion in Rotterdam. However, the impact is heavily dependent on the infrastructure present in the neighbourhood. GO-E archetypes, as used in this research, present real-life grid data for neighbourhoods with varying demand and supply. Within these archetypes, there is a large difference between the impacts of opportunity chargers with different charging capacities.

In this research, three archetypes are tested: post-war terraced houses, post-war tenements and corporation residences. Chargers are included with a rated capacity of 200 kW, representing a mid-range charger, and 450 kW, representing the highest possible capacity. The following conclusions can be drawn:

First, Archetype 3 neighbourhoods, post-war terraced houses, are unable to support 200 kW and 450 kW chargers under most circumstances, as load rates continuously exceed 100%. However, during the summer months, including a 200 kW charger can alleviate grid congestion due to the usage of PV-generated energy before it passes through the transformer to the high-voltage grid. This alleviation was found to a lesser extent in other archetype neighbourhoods.

Second, Archetype 4 neighbourhoods, post-war tenements, are likely to support a 200 kW charger if charging from 18:00 to 00:00 is excluded due to the residents' high energy demand. They will not support a 450 kW charger as load rates continuously exceed 100%.

Thrid, Archetype 5 neighbourhoods, corporation residences, can support a 200 kW charger throughout the day and a 450 kW charger can be supported if charging from 18:00 to 00:00 is excluded.

The inclusion of opportunity chargers and their impact on local grid congestion is therefore highly dependent on the location of the chargers.

SQ4: To what extent can traffic priority for electric buses impact travel time and energy consumption to reduce charging needs and increase charging times?:

Traffic priority can reduce the charging capacity of opportunity chargers by increasing the time spent at chargers, reducing the energy consumed by the EB, and, thus, reducing the height and duration of the peaks on the grid. In this conclusion, the reduction in total travel time has a larger effect (9.8%) than the reduction in energy consumption (4.5%).

Main research question: To what extent is the implementation of on-route opportunity charging possible when considering the mobility and energy systems simultaneously?:

The results presented in this thesis suggest that an EB route design with opportunity charging is impossible without considering both mobility and energy systems simultaneously. Regarding the mobility system, opportunity charging can only be implemented if the charging times and capacity satisfy the energy requirements without interrupting the timetable. Regarding the energy system, opportunity charging can only be implemented at locations where charging capacity is available in the grid at that time. Without traffic priority, it is impossible to satisfy all requirements. Either the charging capacities would be too high for the energy grid or the charging times would be too long for the EB service. Introducing traffic priority allows for the introduction of opportunity charging while satisfying all requirements by reducing travel time, increasing potential charging time, and reducing energy consumption, thus decreasing charging requirements.

The answers to the main research question and subquestions show that an integrated approach to decision-making, including both mobility and energy systems, is required to achieve a bus service with opportunity charging that satisfies all requirements. This is a necessity for creating liveable urban areas in the future.

7.1. Recommendations for further research

This research provides the first integrated approach, including mobility and energy systems, to designing a charging strategy for a case study in Rotterdam. More research is required to create implementable designs for opportunity charging.

Firstly, further research can be conducted into an optimization model for the presented results. The results regarding grid availability in the different archetypes, new charging locations, capacities, and times can be determined, after which an optimal charging strategy and timetable can be calculated. Costs are an important aspect of decision-making for PTOs. This research has not included costs as a research metric, but they are, in reality, a major deciding factor for implementation. This includes costs for infrastructural investments and charging costs, which are required for final decision-making. Furthermore, the case study selected for this research contains a single bus line. Further research can be conducted for multiple bus lines sharing the same charging stations along their route since, in real life, many bus stops are serviced by multiple bus lines. The increase in bus lines for each charger will increase the number of charging events but decrease costs, as opposed to every bus line having its own chargers. Additionally, this research does not include the effects of traffic priority on the other traffic in the area. The increase in travel time and potential energy costs for other users might negatively compensate for the savings for the bus.

Moreover, the results in this research do not include battery capacity or degradation as a contributor to decision-making. Investigating the possibilities of reducing battery capacity due to opportunity charging and the effects this has on consumption patterns is required. Additionally, multiple and sudden high-capacity charging events throughout the day will degrade the battery. Investigation into these effects on batteries is required for real-life implementation.

The results of this research increase the waiting time at intermediate stops, which requires the bus and its passengers to wait for extended periods of time at the bus stop. Further research should include the willingness of people to wait at bus stops and attach a monetary value to this in the decision-making.

Secondly, this research suggests that the PTO is responsible for the decision-making regarding installing chargers and, in the future, the associated costs. However, having publicly available charging stations at bus stops or other locations along roads could benefit other public service operators, such as garbage collectors or delivery trucks. Using the data regarding grid availability in this research, further research should be conducted into sharing the charging stations and their costs for other applications.

Thirdly, the literature suggests that the transformer load rate should not exceed 100% as this degrades the transformers' lifetime and its connected components. However, the results do not provide values for the degradation caused by the opportunity charging. Including degradation in terms of costs will assist decision-making in the future.

Furthermore, the traffic intensity analysis suggests that energy consumption is more related to total distance, as often used in the literature, and less to the number of acceleration and deceleration actions. Further research into the correlation between energy expenditure, travel time and travel distance is required.

Lastly, the RET, the PTO in Rotterdam, includes terminal station charging in its current charging strategy. However, terminal station charging is explicitly not used in this research to focus on opportunity charging as a potential solution. The literature shows that terminal charging, as included by the RET, degrades the quality of the distribution grid. Further research into the effects of the RETs' terminal charging on grid congestion is required.

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A
The impact of a 200 kW charger

The output of Gaia shows the load rate on the transformer every 15 minutes for a generic weekday and weekend day for every month of the year. Figure A.2 displays the load rate of the least impacted transformer with and without a charger of 200 kW of the grid of archetype 3: post-war terraced houses.

Figure A.1 provides examples of how the graph should be read. On the left, a single day is described. The black circle represents the start of the day at 00:00, the red circle represents the morning peak at around 6:00 - 8:00, and the yellow circle represents the evening peak at around 18:00 - 20:00 when people cook, using their heating and other appliances. On the right, multiple days are shown. The full graph represents an entire year. It is represented by a single workday and a single weekday for each month. For example, the red square represents a workday in January, the green square a weekendday in January, the pink square a workday in February, the yellow square a weekend day in February, and the black square represents a weekday in March, and so on for the full graph. Resulting in a total of 24 day-graphs. The orange line represents the 100% transformer load rate. Exceeding 100% is possible, but degrades the equipment more rapidly and should therefore be evaded where possible.

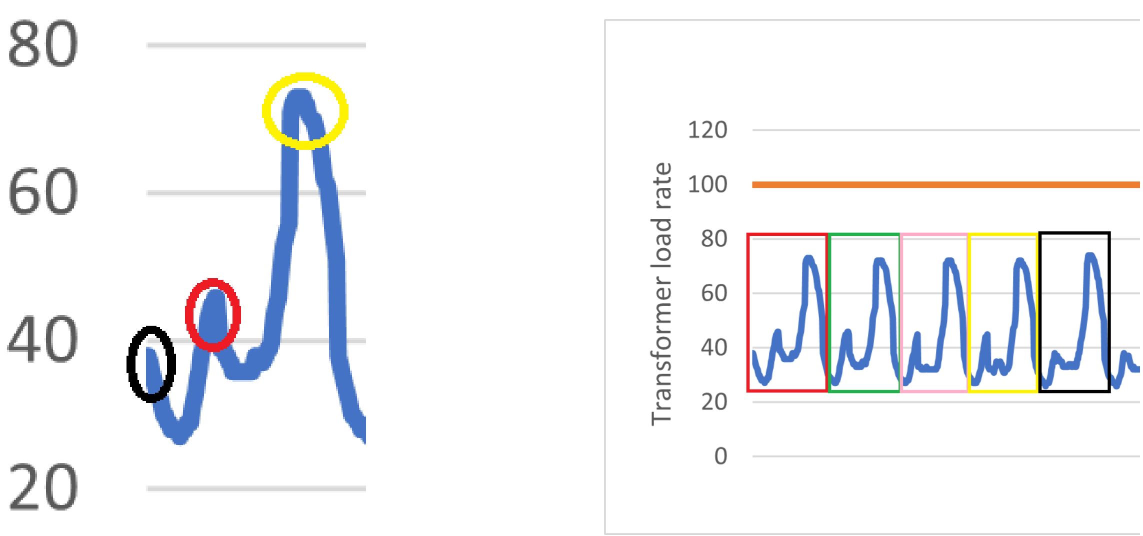

Figure A.1: A tutorial on how to read the Gaia load rate graphs, on the left a single day, on the right multiple days for each month

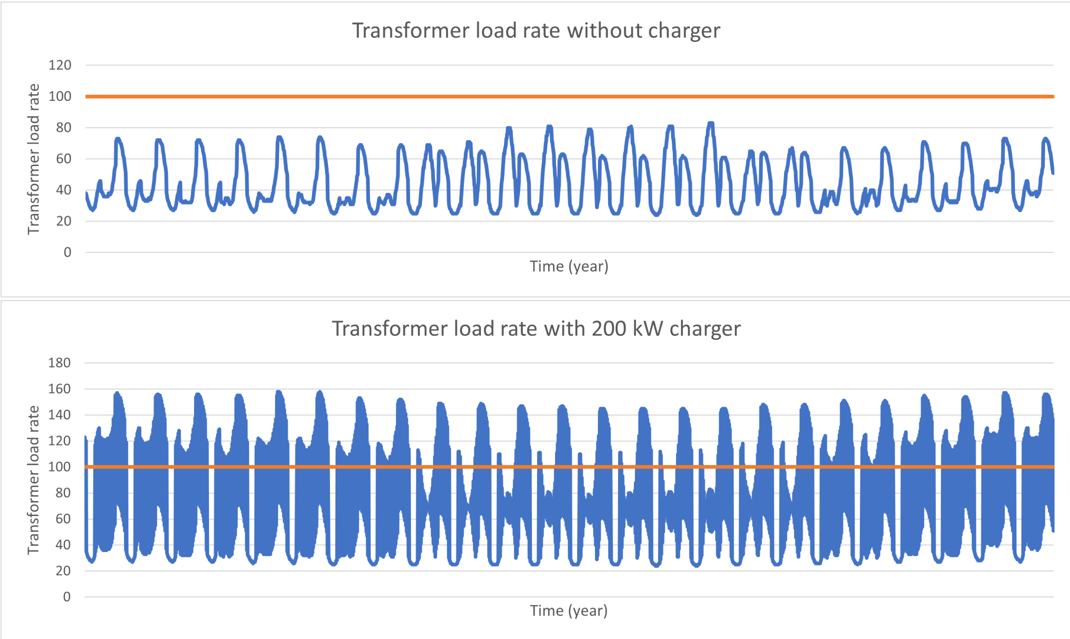

Figure A.2: The transformer load rate of archetype 3: post-war terraced houses without (top) and with (bottom) a 200 kW charger, the blue line are the transformer load rates and the orange line an indicator for 100% load rate

Figure A.3 displays the load rate of the least impacted transformer without and without a charger of 200 kW of the grid of archetype 4: post-war tenements.

Figure A.3: The transformer load rate of archetype 4: post-war tenements without (top) and with (bottom) a 200 kW charger, the blue line are the transformer load rates and the orange line an indicator for 100% load rate

Figure A.4 displays the load rate of the least impacted transformer without and without a charger of 200 kW of the grid of archetype 5: corporation residences.

Figure A.4: The transformer load rate of archetype 5: corporation residences without (top) and with (bottom) a 200 kW charger, the blue line are the transformer load rates and the orange line an indicator for 100% load rate

Figures A.2, A.3, and A.4 show the transformer load rate for a weekday and a weekend day throughout the year. The impact of the charger does change noticeably throughout the day but does not change substantially from month to month. However, the impact of PV modules does make a difference between winter and summer. Therefore the following results will not show a full year, but only single days for winter and summer. For each result, with and without a charger for each archetype, 4 graphs are displayed. One for a weekday in January, one for a weekend day in January, one for a weekday in July, and one for a weekend day in July.

A.1. Archetype 3: post-war terraced houses

Figure A.5 displays the impact of a 200 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (top left), a weekend day in January (top right), a weekday in July (bottom left), and a weekend day in July (bottom right) for archetype 3: post-war terraced houses. The red line represents a 100% load threshold which should preferably not be passed.

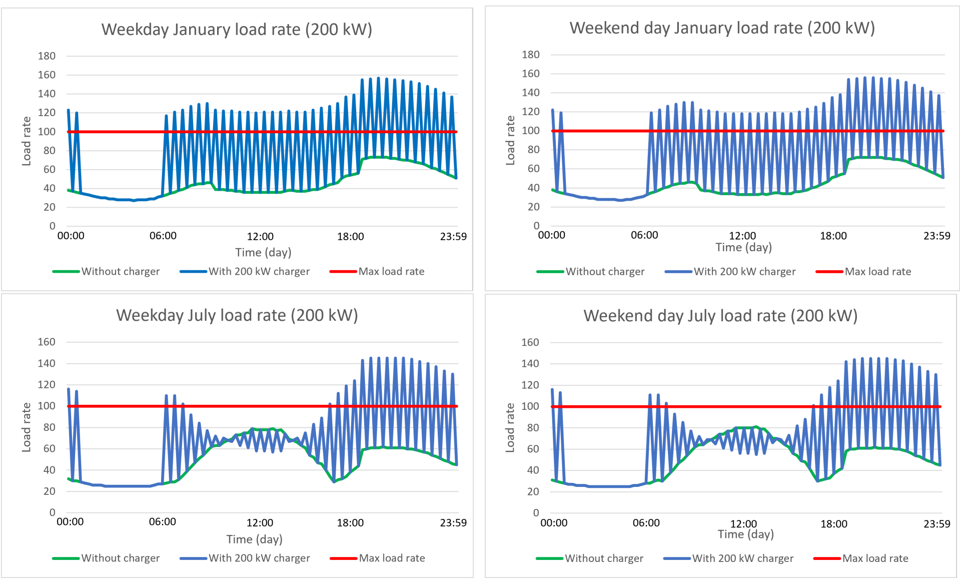

Figure A.5: The impact of a 200 kW charger on the grid of archetype 3: post-war terraced houses

A.2. Archetype 4: post-war tenements

Figure A.6 displays the impact of a 200 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (top left), a weekend day in January (top right), a weekday in July (bottom left), and a weekend day in July (bottom right) for Archetype 4: post-war tenements. The red line represents a 100% load threshold which should preferably not be passed.

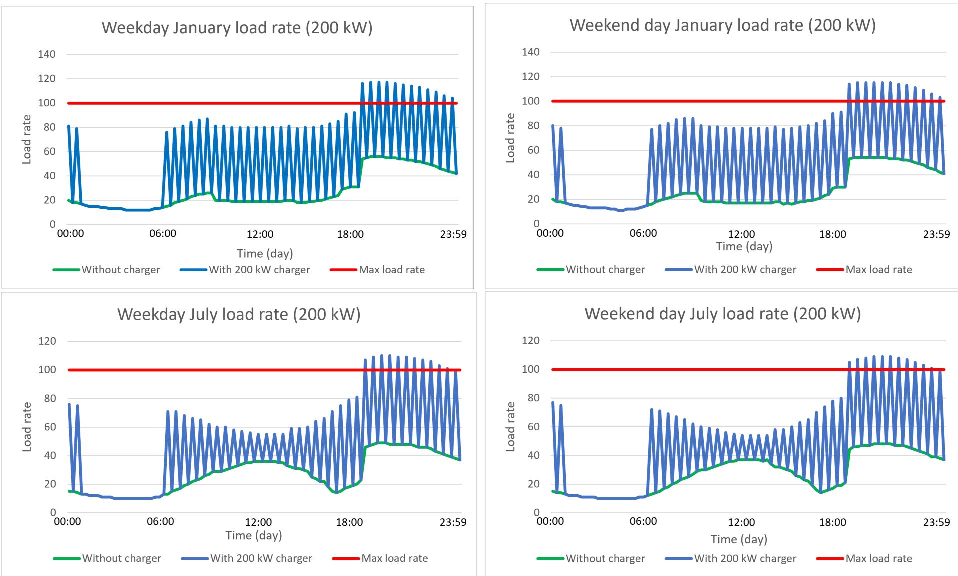

Figure A.6: The impact of a 200 kW charger on the grid of Archetype 4: post-war tenements

A.3. Archetype 5: corporation residences

Figure A.7 displays the impact of a 200 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (top left), a weekend day in January (top right), a weekday in July (bottom left), and a weekend day in July (bottom right) for Archetype 5: corporation residences. The red line represents a 100% load threshold which should preferably not be passed.

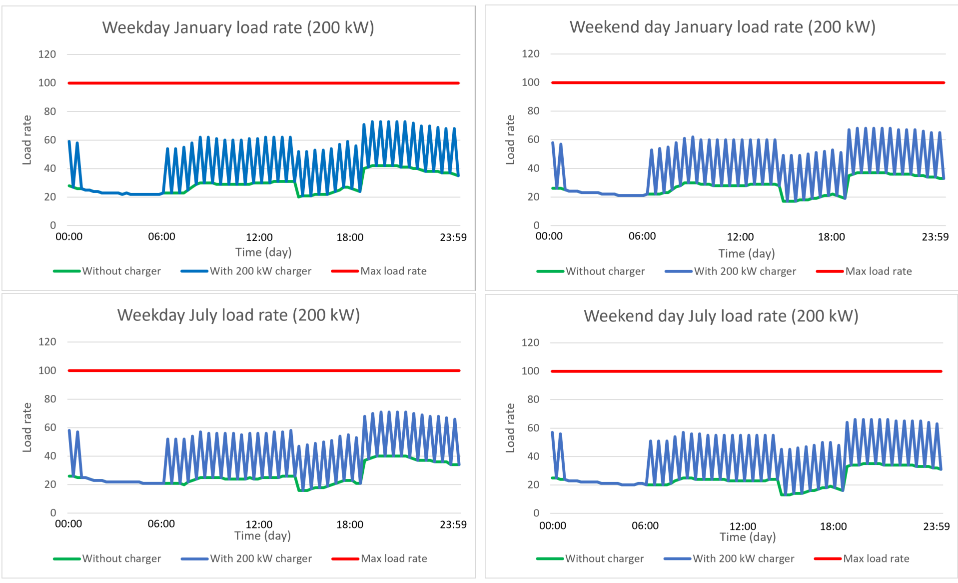

Figure A.7: The impact of a 200 kW charger on the grid of Archetype 5: corporation residences

B
The impact of a 450 kW charger

Due to unnoticeably small differences between the consumption patterns of a weekday and a weekend day in Appendix A, the results of the 450 kW chargers only include a weekday in January and a weekday in July.

B.1. Archetype 3: post-war terraced houses

Figure B.1 displays the impact of a 450 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (left) and a weekday in July (right) for archetype 3: post-war terraced houses. The red line represents a 100% load threshold which should preferably not be passed.

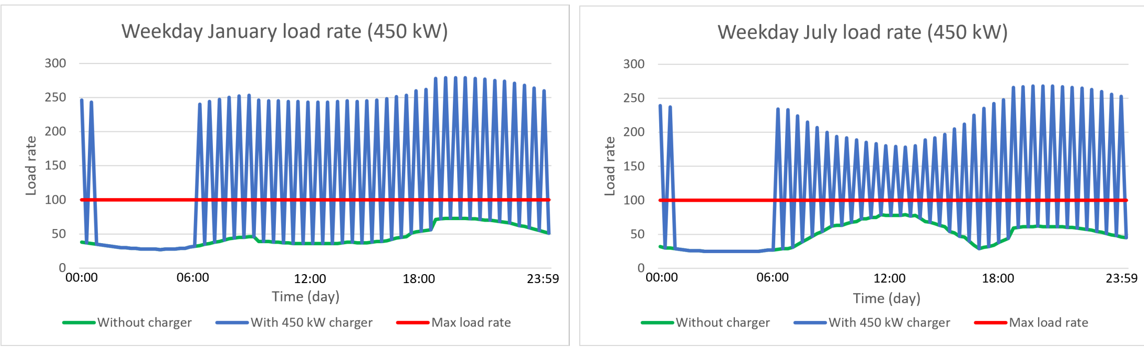

Figure B.1: The impact of a 450 kW charger on the grid of archetype 3: post-war terraced houses

B.2. Archetype 4: post-war tenements

Figure B.2 displays the impact of a 450 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (left), and a weekday in July (right) for Archetype 4: post-war tenements. The red line represents a 100% load threshold which should preferably not be passed.

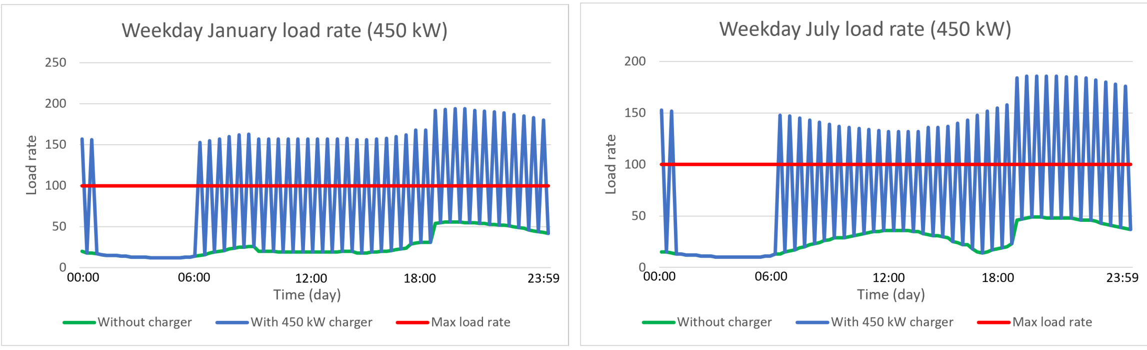

Figure B.2: The impact of a 450 kW charger on the grid of Archetype 4: post-war tenements

B.3. Archetype 5: corporation residences

Figure B.3 displays the impact of a 450 kW opportunity charger on the transformer (blue) compared to the transformer without a charger (green) for a weekday in January (left), and a weekday in July (right) for Archetype 5: corporation residences. The red line represents a 100% load threshold which should preferably not be passed.

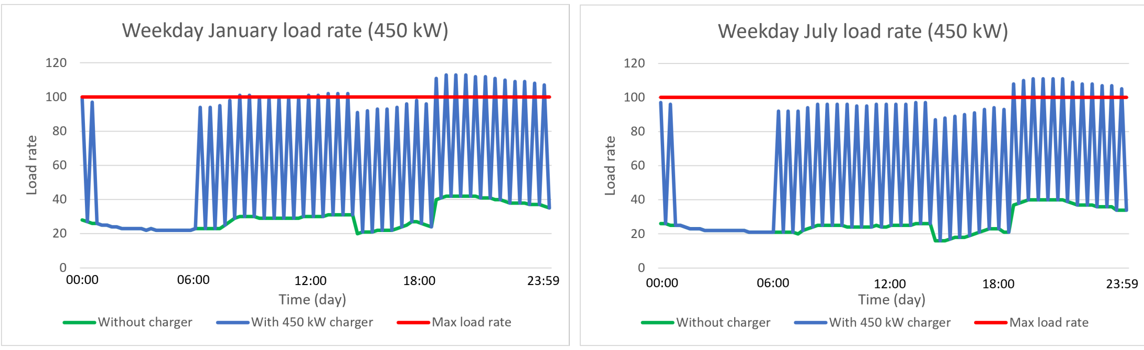

Figure B.3: The impact of a 450 kW charger on the grid of Archetype 5: corporation residences