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Optimal Charging of Electric Buses in an Existing Schedule Utilizing the Day-Ahead Electricity Market

Master's Thesis

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Abstract

In recent years the push to renewable energy has increased substantially. Households are encouraged to disconnect gas lines and install solar panels to create their own renewable energy. Governments are trying to stimulate both households as well as companies to rethink their energy usage and reduce or transition their energy usage. In the case of public transit in The Netherlands, agreements have been made to solely have tank-to-wheel emission free fleets by the year 2030, with the introduction of new vehicles to be tank-to-wheel emission free from the year 2025 onwards.

This thesis report is the product of my research performed at Qbuzz which tries to help them reduce the charging costs of their electric buses. We have compared two different ways of scheduling the charging of the electric bus fleet located at bus depot Remiseweg, Nieuwegein, The Netherlands. The first scheduling is a naive charging schedule. A bus will charge whenever it is at a charging location for as much as possible. The second charging schedule is a smart charging scheduling. This means a bus will only charge if the schedule tells it to. The schedule is optimised using a forty-one hours look ahead algorithm which will schedule the charging to be as cheap as possible, whilst adhering to a set of rules. Using the smart charging algorithm the electricity costs can be reduced by 28.8% to 31.4%. This is the result when the buses drive exactly on schedule. However, in the real world, the buses do not always drive exactly on schedule. This will result in buses arriving earlier or later than planned. To see how much of the expected savings could be realised a simulation of the operations is created. This simulation showed that a savings between 22.0% and 23.9% is to be expected.

Contents

Part I

Background & Methodology

In this first part we will start with an introduction into the topic at hand, see Chapter 1. We will then take a look at the existing literature studies in Chapter 2. After we have discussed the subject at hand including the already performed research, we will state the research question on which this thesis focuses in Chapter 3. We will finish this part by going over the methodology in Chapter 4.

Chapter 1

Introduction

In recent years the transition from internal combustion engine vehicles to electric-powered vehicles has increased its pace, especially in Europe (Paoli et al., 2022; Alsauskas et al., 2023). Battery technology has become cheaper and ranges have increased, which in turn lowered the early adopters' fee, reduced range anxiety and increased the adoption of electric vehicles.

Another reason for this transition acceleration is the care for the environment. Governments are trying to reduce the emission of greenhouse gasses (GHG) to lower the stress put on the environment. The Paris Agreement is the most prominent example of this strive (United Nations, 2015). The European Union strengthens this agreement by forcing all new cars and small vans sold in the EU to be 100% emission-free from 2035 onwards (European Union, 2023).

Businesses, with their vast fleets of vehicles, have a significant GHG footprint. In the year 2015, transportation in Europe was responsible for the emission of 23.5% of the GHG in Europe (European Union, 2017). By switching to an electric fleet the GHG emissions of the transportation sector can be greatly reduced.

One of the sub-sectors responsible for the GHG emissions in the transportation sector is public transport. In The Netherlands this sector has agreed to speed up the transition towards emission-free vehicles. The Public Transport Authority, among other groups, has agreed to only introduce tank-to-wheel emission-free buses from 2025 onwards and to have a tank-to-wheel emission-free bus fleet by the year 2030 ("Bestuursakkoord Zero Emissie Regionaal Openbaar Vervoer Per Bus", 2016).

Unfortunately, the transition to electric buses is not as easy as you might think. As the range of an electric bus, at this time, is shorter than their internal combustion engine counterpart, Public Transport Operators (PTOs) need to adjust their scheduling because the previously optimal schedules have now become infeasible. Besides the range shortcoming, other problems in this transition are refuelling costs, or in the electric bus case recharging costs and refuelling durations. Whilst fuel costs for internal combustion engine buses are relatively steady and the refuelling happens rather quickly, the cost of electricity changes often and the recharging takes multiple hours. This further complicates the transition. In the next two sections we will provide a summary on how the recharging costs and recharging durations have this negative impact on the planned transition.

1.1 Electricity Market

Regular households generally have one or two electricity rates, but big energy consumers can have prices in accordance with the electricity market. The prices in this market fluctuate at a set interval.

This leads to an interesting optimization problem for these big electricity consumers, as they can try to reduce their electricity costs using this price-fluctuating energy market.

The basic idea of the electricity market is as follows. We have consumers who have a willingness to pay. This means that a consumer attaches a certain value to the wanted electricity. For the consumers to get their electricity we need producers. Producers have production costs for the generation of electricity. A producer would like to charge a value higher than their production costs to consumers in order to make a profit. When the market settles, we get an electricity price that is higher than the production costs for producers and lower than the willingness to pay of consumers (Delft, 2019). There are multiple reasons for the fluctuation of electricity prices. One of the reasons is the addition of renewable energy production. As, for example, a windmill has no real marginal production costs for electricity, the market price can be much lower when compared to fossil fuels, which have a higher production cost. Unfortunately, as many renewable energy sources rely on the weather, the production can fluctuate heavily and is therefore not plan-able. As the production is not affected by the demand (not plan-able), the electricity prices created by the market can vary substantially. Another reason for price fluctuations is the demand. When the demand for electricity is high, the electricity producers will have to use more expensive forms of electricity generation, resulting in a higher market price. These are some reasons for the price fluctuation on the day-ahead market (DAM), but they are not the only ones. Some examples of other influential factors on the electricity prices are transmission constraints (bottlenecks in the network can prevent the flow of cheap electricity to places where lots of electricity is needed), market participants (participants use bidding strategies), regulatory policies (policies such as subsidies and taxes) and geopolitical events (such as conflicts which prevent the trade or creation of cheaper electricity).

1.2 Recharging

The recharging of electric buses can be divided into two main categories, depot charging and on-route charging. The chosen recharging method limits the number of possibilities in both the bus as well as the charge scheduling. Depot charging requires the buses to drive back and forth between their trips and the depot, meaning they most likely will have to charge for a longer time to prevent driving to and from the depot after every single trip, as driving to the depot after each trip is most likely not optimal. On-route charging enables small recharging events, which can result in a smaller fleet of buses, as they will not need to drive back to the depot to charge. As the fleet of buses is smaller, there are fewer buses to make an optimal schedule.

Depot charging is usually performed overnight. At the end of its shift, the bus will come back to the depot and charge during the night. This type of charging usually occurs at around 50 kW. This means that in one hour the battery can charge 50 kW, resulting in an increase of battery charge by 50 kWh. If we take an average battery consumption of 1.3 kWh/km as found by Beckers et al. (2021), a single charge of one-hour results in a range extension of around 38 km. When the charging time is reduced to fifteen minutes, the added range is around 9.5 km. Do note that depot charging can occur during the day. However, due to the typically slow charge rate, this will not be enough to quickly add the range needed to perform another round trip before arriving back at the charger when using just enough buses to service the route. If there are extra buses that, for example, drive during the rush hour, then slow charging during the day is more likely to occur as buses can have longer charging times.

On-route charging is charging performed during the shift of the bus. Occasionally a bus has to wait for some time before departing from a particular stop. Examples of this are bus stops at the end of a route or layover points, such as a train station. During this time the bus may recharge its battery and afterwards continue its shift. Typically, this type of charging occurs at rates of 300 kW and more. Taking the same average battery consumption of 1.3 kWh/km as we have done before, we now get a range extension of 58 km in just fifteen minutes. We see that by allowing quick charging during the shift, batteries can generally be smaller than the batteries in a bus using the slower overnight charging method, as we are able to extend the range enough to perform a round trip and recharge again before the battery is fully depleted.

The goal of this research is to optimize the charging of electric buses in an existing bus schedule using the day-ahead electricity market so that the electricity costs are reduced and the bus schedule remains unchanged. A reduction in electricity costs results in lower operational costs. This would allow for an easier transition towards an emission-free vehicle fleet as the long-time costs will be reduced. What makes this research unique is the addition of the validation of the smart charging results, giving a clearer view of the expected cost reduction.

The rest of this thesis report is modelled in the following way: in Chapter 2 we will be going over the existing literature. This will be followed up by a description of the problem we will research in this thesis. After which we will end this part with the proposed methodology. In Part II we will briefly discuss the datasets we will be using in this research. Part III shows the implementation of the proposed research, consisting of both the charging modes and the validation of the results. Part IV concludes this thesis report by discussing the results and giving a conclusion to the research conducted.

Chapter 2

Literature Overview

2.1 e-VSP

The Vehicle Scheduling Problem (VSP) is a well-known, intensively researched and polynomial solvable problem (Bunte and Kliewer, 2009; Perumal et al., 2022). The VSP is about scheduling vehicles so that all trips are done exactly once and the costs associated with this schedule are minimized. When solving a VSP for public transport, we have to deal with fixed departure and arrival times. Besides making sure that all trips are performed, the objective is to minimise operational costs. The operational cost is the sum of the fixed cost per vehicle used and the variable cost per kilometre for fuel, crew and maintenance. The electric VSP (e-VSP), which is an adaptation of the VSP, has become of greater interest in recent years, as many companies want or need to electrify their fleet. The biggest difference between the two scheduling problems is the range variable. In the VSP the general assumption is that a vehicle can perform the proposed schedule without running out of fuel, whereas in the e-VSP the range limitation plays an important role in the possibilities of the schedule. When an electric bus reaches its range limit, the bus in the e-VSP will need multiple hours to fully recharge its battery. These extra limitations may result in valid vehicle tasks for the VSP being invalid when solving the e-VSP variant.

To prevent electric vehicles from running out of fuel, they need to be recharged on time. There exist two main options for this, namely battery swapping and regular battery charging, where regular charging is comparable to charging your phone. You charge it by hooking up your charger to your phone instead of swapping the battery and charging the empty battery without it being inside the phone, as battery swapping would do. Chao and Xiaohong (2013) considered the battery swapping problem for a bus depot in Shanghai, China. They used two independent objective functions: one function to minimize the capital investment and one for the charging demand in the swapping stations. To solve the problem, a modified multi-objective optimization method adopting the basic idea of a Non-dominated Sorting Genetic Algorithm was used. They concluded that due to the drawbacks of short ranges and long recharge times, bus routes with short daily trip distances and fewer bus stops are advised. For our problem, we will not be using battery swapping stations, as the infrastructure is already in place to charge the buses themselves.

Recharging a bus happens at a charging location. The placement of the charging locations can be seen as an optimisation step in the e-VSP problem. On the one hand, we want the chargers to be at a location such that the overhead times to get to and from the charging station are as low as possible. On the other hand, we want to minimise the costs for a charging location, as charging locations on busy roads are more likely to be expensive compared to charging locations in quieter places. Lastly, we want to minimise the needed number of charging locations, as more charging locations cost more money. Kunith et al. (2014) created a mixed integer linear optimization model to minimize the number of charging stations required for a bus line. To make the research more applicable, they took the existing bus operations into account as well as the charging process and different electricity consumption rates, which are able to differ thanks to traffic congestions and weather conditions. Xylia et al. (2017) created an optimization model where the waiting times of the vehicles at bus stops and at the depot were used to optimise the charging locations. If a bus is likely to be present at a certain bus stop for a longer period of time, this location would be highly favourable to get a charger, as the schedule does not need to be changed to charge the bus. They used multiple charger types to best suit the locations and thus tried to reduce the costs even more. They also enabled the model to optimise multiple bus lines together instead of the separate approach.

Besides the charger locations and the type of charging used, there is another choice to be made regarding the charging: Do we allow opportunity charging? This means that instead of having to charge the battery to 100% each time we recharge a bus, we can partly recharge the bus. Van Kooten Niekerk et al. (2017) created a deterministic e-VSP model using Integer Linear Programming (ILP) which allowed for opportunity charging. Besides this, they also implemented a non-linear charging curve, as batteries do not charge linearly, but rather depending on their State of Charge (SoC) level. Lastly, they also considered both time of use (ToU) pricing and depth of discharge (DoD) effects on the battery. Due to the large number of possibilities for such an ILP, Van Kooten Niekerk et al. chose to speed up the algorithm using column generation in combination with Lagrangian Relaxation. Thanks to these changes, they made a model which is tractable in a reasonable time. Ten Bosch et al. (2023) compared four algorithms that create a pre-selection of subsets of trips used to solve the e-VSP using an ILP. The algorithms had to reduce the DoD in order to reduce battery depreciation. They allowed opportunity charging, resulting in an easier reduction of the DoD as they are able to add some electricity whenever there is a small charging window. Using Column Generation in combination with Linear Programming and LP-relaxation, they found the lower bound to the optimal solution, whereafter they compared it to Column Generation with Integer Linear Programming, Simulated Annealing with multiple starts and local search with recombination through ILP, where the input for the ILP is found using Simulated Annealing. Using their Simulated Annealing approach to create a pre-selection of subsets of trips, they were able to find solutions with a cost that is at least 1% lower (times the total cost) than the cost of the solutions found using Column Generation.

2.2 Electricity Consumption

Another important characteristic of the electric bus is the electricity consumption. Whilst an internal combustion engine bus is able to drive the full schedule regardless of external factors like traffic, weather, driving style and other factors, an electric bus has a much shorter range and needs to be careful with consumption fluctuations caused by external factors.

De Bruin (2022) used three different driver profiles to determine the electricity consumption. One profile with below average, one with average and one with above average electricity consumption. To create a more realistic model, the drivers were allowed to swap at the end of a trip after 2 hours have passed since the last driver swap. This could result in a different electricity consumption for each driver swap, but it does not have to as there are only three consumption profiles available.

They showed that improvements on the solution quality of up to 3% were possible. Some instances were not able to find a solution within the given time limit, but the instances which did showed improvements to the best solution quite quickly, according to De Bruin.

Gao et al. (2018) performed an analysis on the historical data of a PTO in Baoding, Hebei Province, north China. They concluded that the most important factors for electricity consumption were: day of the week, weather conditions (such as temperature, haze or rain), length of travel, air conditioning and the vehicle running limit policy. Vepsäläinen et al. (2018) and Wang et al. (2020) found that to accurately resemble the electricity consumption it is better to split the modelling of the electricity consumption into seasons, to keep the characteristics of each season in mind. Lampropoulos et al. (2022) noted after extensive desk research that the factors ambient temperature, wind speed and day of the week were the most important for energy consumption. This research covered the operational area Drechtsteden-Molenland-Gorinchem which is located in The Netherlands.

2.3 Battery Degradation

Besides electricity consumption fluctuations there also is battery capacity degradation. As a battery gets charged and discharged it loses a bit of its capacity. There are some factors that will make this loss greater for a charge cycle, such as deeply discharging a battery. Van Kooten Niekerk et al. (2017) stated that when the DoD is greater, meaning that the SoC level gets lower, the expected lifespan (the number of full charge cycles) of the battery drops as well. They created a function which models the effect of the DoD on the life expectancy of the battery. De Bruin (2022) incorporated the degradation using the DoD effect function by Van Kooten Niekerk et al. into their model.

Zeng et al. (2022) proposed a function to formulate the unit wear cost for cycling a battery in the specific SoC range of a bus based on a certain DoD. They used this to create a relationship between battery ownership costs and unit wear costs for each bus. They added the daily charging costs to this formulation to create the objective function. They showed that ignoring the wear cost in the objective function increased the wear costs by 4.2%. This was done whilst restricting the SoC levels to the range of 30% to 90%. When setting this range to 0%-100% the wear costs increased to 25.6%, which is ten times the charging expenses even with a 10.89% drop in charging costs. They noted that this result indicates that setting the proper SoC interval can effectively control the wear cost of the battery when the battery degradation is not considered.

2.4 Bus Rostering, Charge Scheduling and Charge Management

Besides a full e-VSP problem, sub-problems have also been tackled. The focus can, for example, be shifted to bus rostering and charge scheduling using blocks, as Rojas and Santiago (2022) have done. This problem consists of assigning a fleet of electric buses to vehicle blocks and scheduling the charging operations. Rojas and Santiago created a mixed-integer linear program (MILP) taking into account the ToU prices of electricity. This model worked with deterministic driving times, recreating the ideal world. They created vehicle blocks consisting of a predefined sequence of trips for a whole day instead of singular trips that need to be scheduled as a day schedule. They were not able to find an optimal solution within two hours, but they did gain managerial insights to help PTOs make better operational decisions from an operational cost perspective.

Besides the scheduling of charging, there also is the possibility to manage the charging, an often overlooked aspect. This means that we are able to determine with how much power we charge the buses. This is especially important with the addition of fast chargers, in which case the peak power consumption can quickly, significantly rise resulting in higher contract costs. Besides determining the charging power, charging management allows to change the charging times. This means we can start charging at a later time than planned, stop earlier than planned or not charge at all. Rojas and Santiago (2022) implemented this feature to reduce the peak power consumption and thus also reduce the contract costs in this manner. Liu et al. (2021) created an ILP with Column Generation to solve the charge scheduling and management problem. First, they took the average electricity consumption per minute on a day. Then, they put these average values into five different time periods and gave each block its corresponding electricity usage. The optimization model takes the electricity consumption for the created time periods, so it does reflect the real world to some extent, but the modelling is still a rather deterministic approach as each day the electricity consumption is the same at a specific time. Jahic et al. (2019) addressed the peak load minimization sub-problem. They allowed for three different power consumption rates to represent charging, preconditioning (heating the bus before departure) and charging with preconditioning. Using a heuristic model they were able to reduce the peak load with 42.6%, theoretically. Due to the focus on this sub-problem, they did not take other operational costs, such as the ToU electricity costs, into account. This means the reduction in peak load could have resulted in more expensive electricity usage. Liu et al. (2022) solved the charging scheduling problem using an ILP model with stochastic driving times. They noted that the stochasticity of trip travel times results in longer charging times and higher electricity costs. They do use ToU energy pricing, but they neglect both the stochasticity of battery usage and battery charging management. Leou and Hung (2017) took blocks of 15 minutes to represent the time unit in their model. This choice was made because their electricity provider calculates the contracted electricity capacity based on 15 minutes. They implemented a limit on the total charge at a given time, to represent the limitations of the charging infrastructure and the contract with the electricity provider. To not be fully deterministic, the start and end SoC levels are determined by a Gaussian distribution of the deterministic start and end SoCs of the battery. Yang et al. (2018) focused on creating an optimal charging schedule for wirelessly charged electric buses. To make this schedule cost efficient they paid attention to if the buses can use the reserved electricity, as not using this reserved electricity results in imbalance costs, which in turn makes the schedule more expensive. To solve the problem, they created a two step algorithm where the first step is calculating the size of the reserved wholesale electricity and the second step is optimally scheduling the charging using this reserved size. They showed that using their approach they were able to reduce the electricity cost by 11% to 18%. Nageshrao et al. (2017) modelled the energy consumption model on the basis of historical data by using a neural network to predict the power consumption. They focused on the battery charging costs, battery health and limiting the maximum total power consumed at a given time. By using indicative data they were able to achieve a cost reduction between 32% and 54%. This, however, is no field data, so it is unsure how accurate the results are when using this model on real operation data.

Chapter 3

Thesis Outline

3.1 Research Question

This thesis is a case study focused on Qbuzz (n.d.). Qbuzz is the PTO in Region Utrecht, The Netherlands. Qbuzz is transitioning from internal combustion engine vehicles to electric vehicles. To aid this transition they want to optimize their operations to reduce their costs.

We can now define the main research question of this thesis, which is stated as follows:

Does the scheduling of charging moments and quantities in an existing bus schedule using day-ahead market information lead to a difference in electricity costs compared to the initially scheduled charging moments and quantities?

3.2 Problem Description

To give a clearer view of this thesis project, we will quickly take a look at the project description. This research will focus on the scheduling of the charging events and quantities in an existing bus schedule. This means each bus has a set of trips it needs to drive and possibly time between these trips. In this thesis, we will not alter the set of trips each bus needs to drive, we will solely focus on scheduling the recharging events and quantities. There already exists a schedule with planned charging events. The existing schedule is made with the worst case scenario values for electricity consumption and battery capacity, without consideration of the ToU prices and may charge at the highest possible rate, so it might not be optimal, but it will, most likely, be feasible. What we plan to do in this project is to schedule the charging events and quantities using the actual ToU pricing to optimise the recharging of the buses.

This problem is an optimization problem in which we want to minimize the operational costs using charge scheduling and charge management. The costs we will focus on are the charging costs and the battery costs. Battery costs are reduced indirectly, as we will keep the SoC between certain values to improve the battery life and in turn reduce battery costs, as stated by Han et al. (2014).

Naturally, there are limitations to this optimization problem. The biggest limitations of this project are the charging power of the charging facilities and the trip schedule of a bus. Chargers are rated for a certain throughput and thus limit the speed at which we can charge a bus. The trip schedules are another limitation in the optimization of the problem as we are unable to move these trips. This means that there are certain time windows in which the bus will not be able to charge, possibly eliminating better solutions in the process. We need to make sure that the trip schedule is still feasible after planning the charging events, so we will validate the created charging schedule by simulating the trips and electricity usage for each trip taking into account external factors such as wind speed, air temperature and rainfall.

3.3 Literature Contribution

We see that previous work was mostly centred on the deterministic scenario. Besides the full planning and charging schedule, there has been some work on rearranging the charging to make the existing schedule less costly (Yang et al., 2018). Stochastic research on this topic is less present. This thesis will contribute to the existing literature by exploring the difference between the existing charging events and quantities and the scheduling of charging events and quantities utilising the day-ahead market for electricity pricing. We follow this up by validating the generated charging schedule using stochastic driving times and electricity usages to see how feasible the proposed planning and difference in cost is.

3.4 Case Study Location

As stated before, this research is a case study for Qbuzz. It is performed on electric buses driving in Utrecht, The Netherlands. We will give a short overview of the electric bus lines we will look into. The information presented in the following subsections is from the operations of spring 2022.

3.4.1 Bus Type

The buses used in this research are all of the same type, which is the Heuliez GX 437. This is an electric bus with a length of 18 meters and a passenger capacity of 140 people. The bus can charge using the overhead pantograph or the CCS Combo2 socket. The battery capacity of the bus is 250 kWh and the worst-case energy consumption, as stated by Heuliez, is rated at 2.08 kWh/km.

3.4.2 Bus Lines

We will focus on three lines operating in Utrecht, namely lines 3, 7 & 8 which are operated by 35 buses. The routes of these bus lines are shown in Figure 3.1. Line 3 has a 12 kilometres long route and goes from Utrecht Central Station to Overvecht and back in one trip, creating a ring shape, with a distance of 250 meters between their quick charger (Facility 2) and their start terminal. This line is serviced in both directions, meaning both clockwise and counter-clockwise. Line 7 has a route between 12 and 13 kilometres long and goes from Zuilen to Westraven or in the other direction with a distance of 1 kilometre between their quick charger (Facility 1) and their start terminal. Line 8 has an 11.5 kilometres long route and goes from Lunetten to Wilhelminapark or the other direction with a distance of 0 meters between their quick charger (Facility 3) and their start terminal as the charger is located at their start terminal. The current charging moments differ between both lines and buses. They sometimes charge after each round trip using quick charging for 5, 10 or even 20 minutes, but at other times they will charge at the depot (Facility 4) after driving several round trips. Note that the given distances to a charger are the distances to their specific charger on the road, as each bus line has its own roadside charging facility. The distances to the depot, where the (overnight) slow charging happens for all the previously mentioned lines, are different.

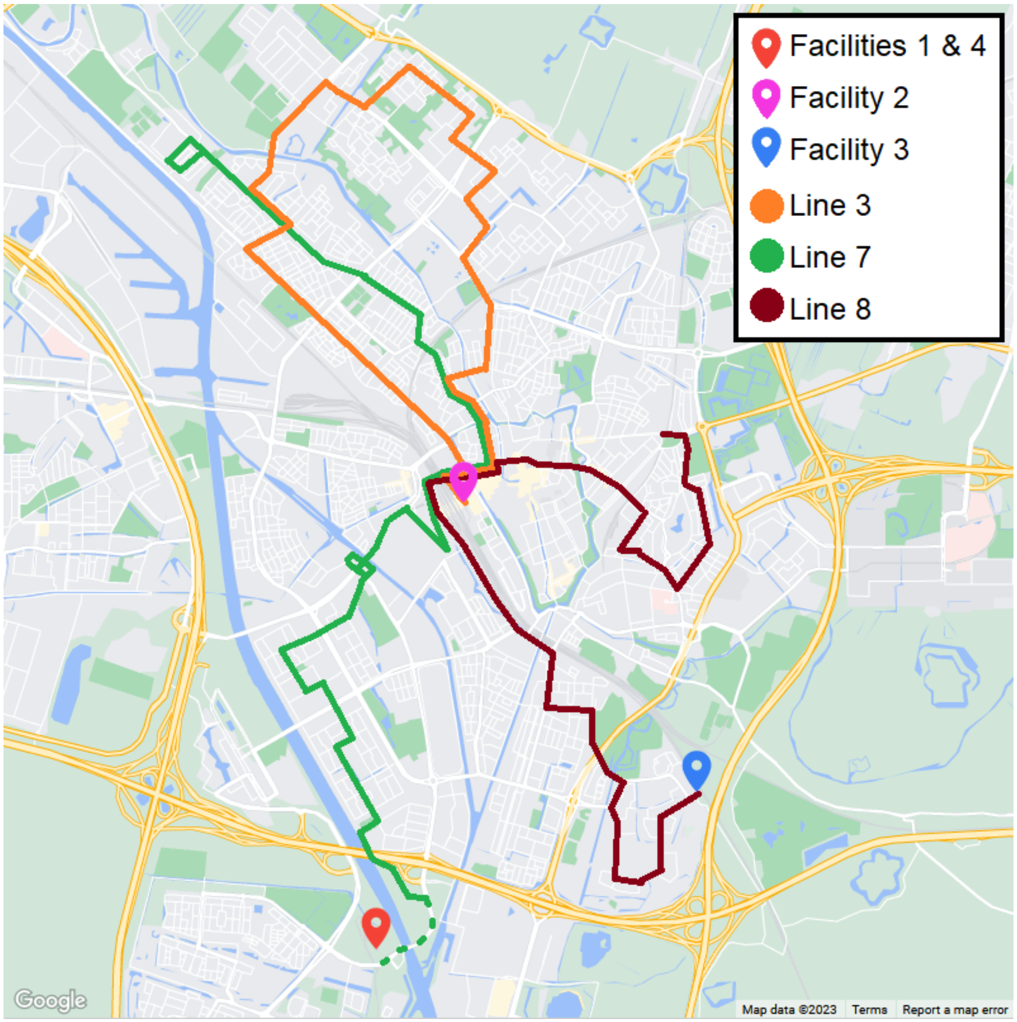


Figure 3.1: A map of the bus routes and charging facility locations. The dotted line of line 7 shows the path towards its charging location.

3.4.3 Charging Facilities

There are four charging facilities for the three lines. The locations of these facilities are shown in Figure 3.1. Charging rates for each facility are dependent on the SoC level of the bus. The charging rates of each facility together with its capacity are presented in Table 3.1. The percentage presented at each rate dictates the SoC level in-between which the given charging speed is available. Charging facility four is a slow charger which is primarily used for nighttime charging of the buses. You might notice that one charging facility does not charge to 100%. Fully charging a battery mainly happens during nighttime charging and is done to help with battery life due to the slow charging speed of a battery for the final 10%. The other chargers charge to 100%, but the final 10% is at a much lower charging rate. Figure 3.2 also presents the charging rates.

Facility	Capacity	rate 1		rate 2		rate 3	
1	6	0-90%	250 kW	-	-	-	-
2	2	0-90%	350 kW	90-95%	240 kW	95-100%	40 kW
3	2	0-90%	350 kW	90-95%	240 kW	95-100%	40 kW
4	36	0-75%	40 kW	75-90%	30 kW	90-100%	20 kW

Table 3.1: Charging Speeds and Limits

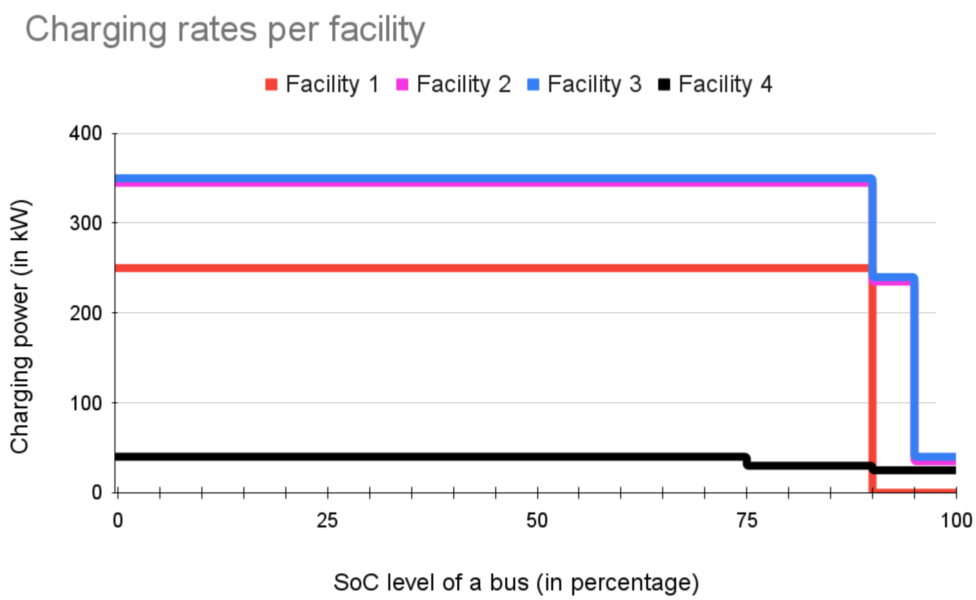


Figure 3.2: The charging rates for each facility.

Chapter 4

Methodology

4.1 Models

This thesis consists of three different models. We start with a deterministic model employing standard charging. This means that it will use a static electricity usage per kilometre and follow the schedule with zero delays. It will charge as soon as the bus arrives at a charger and it will charge at full capacity until either the battery is full or the bus has to leave for its next trip. This model will represent the current situation. The second model will be largely the same as the first model except this time the charging strategy will use the day-ahead market to schedule the charging events and charging speeds so that the electricity costs are minimal. The final model will validate the second model. This model will use stochastic driving times, stochastic electricity usages and the charging schedule created by the second model to see how feasible the proposed charging schedule is and give an idea of the feasible cost reduction. Due to the stochastic nature of this model, we can have a lower SoC than expected in the second model. We try to fix this by charging this missed charge as soon as possible at, presumably, a higher electricity cost.

The first model is only allowed to charge at the already planned moments, whereas the second and third models are allowed to put recharging events in between trips where the gap is big enough to put one, but there is not one as of yet. This enables the models to charge whenever possible, possibly at cheaper times. Lastly, the models will try to reduce the DoD, and its associated costs, to increase the battery life. This is achieved by setting a lower SoC limit, which can be broken at a certain cost.

The second model gets the ToU prices for the next day each day at 1 PM as the ToU prices get published at 1 PM in The Netherlands. To make sure the created schedule is feasible, the model will try to optimize the recharging events from 1 PM on day x up until 6 AM on day x+2, which is 41 hours ahead. If we do not do this the SoC levels of a bus might become too low to make a feasible schedule the day after. For each x we save the first 24 hours. This will become the charging schedule created by the second model.

Finally, due to warranties, each bus will have to charge to 100% SoC each day.

4.2 Travel Times

For the deterministic travel times, we will be using the times presented in the bus schedule. Unlike the bus schedule presented to the passengers, this bus schedule also has the times for a pull-in (arrival) and pull-out (departure) at a depot and, in the case of Qbuzz, times for recharging.

The stochastic travel times need a bit more work. For this, we will use previously seen travel times. We will start by splitting up the day into several segments to suit the different planned driving times. Just as De Bruin (2022) has done, we will divide the day into seven different periods. Then, for each period we will create a scatter plot of the driving times. The driving times are split up into the difference between the planned and realised departure times. This way the influence of departure time on travel time can be seen. For example, a bus is supposed to travel 20 minutes. It however departs two minutes later than planned. Due to the later departure time, there are more passengers along the road, as the passengers who would have come two minutes too late are now on time. The delay caused by more people entering and exiting the bus results in the driving time becoming two minutes longer than planned. The realised travel time is therefore twenty-two minutes. This means that the travel time in the plot will be set to 110%. As the bus departed two minutes later than planned, it will be set at plus two on the x-axis. Figure 4.1 shows a small example of such a scatter plot with this instance added. When simulating the driving times we will first choose if there is a difference in departure time from the planned one and then use a driving time in accordance with the departure difference found in the scatter plot

Lastly, weather data from the Royal Netherlands Meteorological Institute (KNMI) will be used to check for correlations between weather circumstances and trip travel times. If correlations are found, they will be implemented in the stochastic trip times. Correlations might be rainy or windy days leading to 5% longer trip times or sunny days leading to trip times being shorter by 10%.

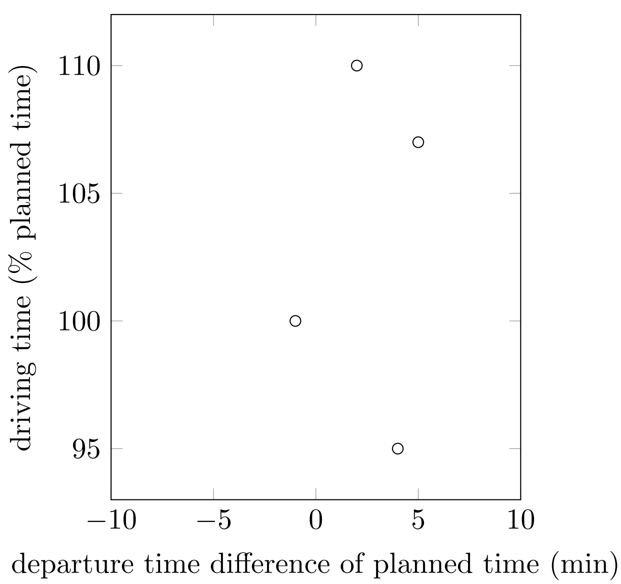


Figure 4.1: An example scatter plot with the given instance added.

4.3 Electricity Usage

For each model, the electricity usage needs to be estimated and the charging has to be planned. For the deterministic model, the electricity usage and charging rates are static. The electricity usage will be calculated using the travel data, meaning the distance travelled. With this, the SoC can be calculated using the PTO-provided efficiency of the bus. We use the PTO-provided efficiency as this efficiency makes sure the schedule is feasible in the deterministic case. Lastly, the charging amount will be calculated using the given start and stop times of an activity and the charging rates as seen in Section 3.4.3.

The stochastic electricity usage will be simulated in a similar manner as Lampropoulos et al. (2022) have done. The stochastic model will use Monte Carlo Simulation to simulate the electricity consumption under different conditions using previously seen electricity usages. These variables are temperature, wind speed, rainfall, time, day and season of the trip.

4.4 Day-Ahead Market

An important aspect of this research is the cost of charging, which will use the DAM pricing. The DAM states the ToU prices. The data used in this research will be the previous pricing gathered from ENTSO-E (ENTSO-E, 2023). ENTSO-E is the European association for the cooperation of transmission system operators for electricity. The data has a set interval of one hour, meaning every hour a different price can be charged. In the year 2022, electricity prices skyrocketed due to the war in Ukraine, amongst other factors. We do not know when the electricity price will skyrocket once again if it ever will. This leads us to use ToU data from the previous three years (2020-2022). By using multiple years, we can see what could be saved when the electricity prices are relatively steady and when they fluctuate heavily.

4.5 Seasons

Previous work detected a large difference between summer and winter electricity consumption (see Section 2.2). The bus schedule also differs between the seasons to accommodate for the difference in electricity consumption. During the summer, the air-conditioning is used to allow for pleasant temperatures inside the bus, whereas during the winter the heater is turned on. Spring and autumn are seasons in which generally neither the air-conditioning nor the heater is turned on, reducing the auxiliary electricity consumption. Besides the difference in electricity consumption due to auxiliary devices, the battery behaviour is different at different temperatures. Due to this difference, we take the season into account.

Part II

Data Analysis

As stated in Sections 4.2 and 4.3 we will be using real-world travel times and electricity usages for this research. To model our stochastic travel times we will be using previously seen travel times to create new travel times. This way the used stochastic travel times are more representable for this case study, rather than generating purely random travel times. This also applies to the stochastic electricity usages, where we will be using real-world electricity usages to create the stochastic electricity usages instead of purely randomly generating our own.

In order to simulate the stochastic electricity usages in a similar manner as Lampropoulos et al. (2022) have done, we will also need to fetch weather data, as these variables seem to be important for the electricity usage, as stated in Section 2.2.

Finally, we will use the DAM pricing, as stated in Section 4.4, as the electricity prices for this research. This way we are able to attach real-world prices to the costs for all the models, giving us a representable cost value for each model.

Chapter 5

Qbuzz Datasets

The first data source we will take a look at is Qbuzz. Qbuzz has provided us with the needed bus data. Think of the planned bus schedules, the realised bus schedules, the charging schedules and the realised charging data. In this chapter, we will take a quick look at these different data sets.

5.1 Line Statistics

We start by taking a look at the realised bus schedule. Due to unforeseen circumstances, Qbuzz might had to deviate from the planned bus schedule. This can happen due to delays, reroutes of trips and technical difficulties. Besides deviations from the planning, the logging of the realised trips is not always correct. Due to these factors the realised schedule does not fully reflect the planned schedule. To make sure this research is adequate, we will need to remove the trips which have not been driven by the buses we are studying. We will say that such a trip is performed by a bus with the wrong busnumber. Besides the removal of these trips, we also need to remove trips which do not have correct loggings. These wrong loggings can be due to missing start or end punctuality, missing busnumbers or missing multiple of these data points.

In Table 5.1 you can see the number of trips before and after filtering. Trips are removed as there was no vehicle number to be associated with the trip, there was no departure or arrival punctuality registered at the start or end of the trip or the vehicle number associated with the trip did not belong to any of the buses we are interested in.

Bus line	3	7	8
trips before filtering	57.763	56.527	56.347
trips removed	15.869	13.946	15.491
missing start punctuality	*1.293*	*1.665*	*1.183*
missing end punctuality	*1.853*	*1.924*	*1.705*
missing busnumber	*102*	*96*	*126*
wrong busnumber	*8.650*	*7.306*	*9.280*
missing multiple data points	*3.971*	*2.955*	*3.197*
trips after filtering	41.894	42.581	40.856

Table 5.1: Line stats

Table 5.2 shows a different overview of the trips and the ones being removed. Besides seeing the number of trips, we have split the data into the seasons. We can see that during the spring we have the highest amount of usable data with all bus lines well over 10.000 trips after filtering.

Line	3	7	8
trips before filtering	57.763	56.527	56.347
spring	*14.585*	*14.316*	*14.329*
summer	*13.328*	*12.892*	*12.849*
autumn	*14.833*	*14.664*	*14.573*
winter	*15.017*	*14.655*	*14.596*
trips removed	15.869	13.946	15.491
spring	*2.052*	*1.843*	*2.625*
summer	*3.703*	*2.974*	*2.968*
autumn	*4.243*	*4.182*	*3.779*
winter	*5.871*	*4.947*	*6.119*
trips after filtering	41.894	42.581	40.856
spring	*12.533*	*12.473*	*11.704*
summer	*9.625*	*9.918*	*9.881*
autumn	*10.590*	*10.482*	*10.794*
winter	*9.146*	*9.708*	*8.477*

Table 5.2: Line stats

Finally, we will take a look at the spreading of the trips after filtering over the day, see Figures 5.1, 5.2 and 5.3. In the histograms, we show the number of trips sorted according to their starting time. In these histograms, we can see the rush hours between 7 to 9 o'clock and 15 to 18 o'clock.

An exception to this is the summer, as there are no real rush hours visible in the data. This can be explained by the season. As it is summer, most people have their summer holiday, including their own bus drivers. This leads Qbuzz to scale down their operations, as people do not need to go to work or school with public transport, therefore reducing the visibility of a possible rush hour.

We see that during the winter there are fewer bus trips, which you would not expect as the weather gets worse and people tend to choose public transit over getting wet or cold. The reason for this is the applied filtering. Apparently, during the winter the logging was the worst of all seasons, leading to a lower number of usable trips, resulting in the histograms looking this way.

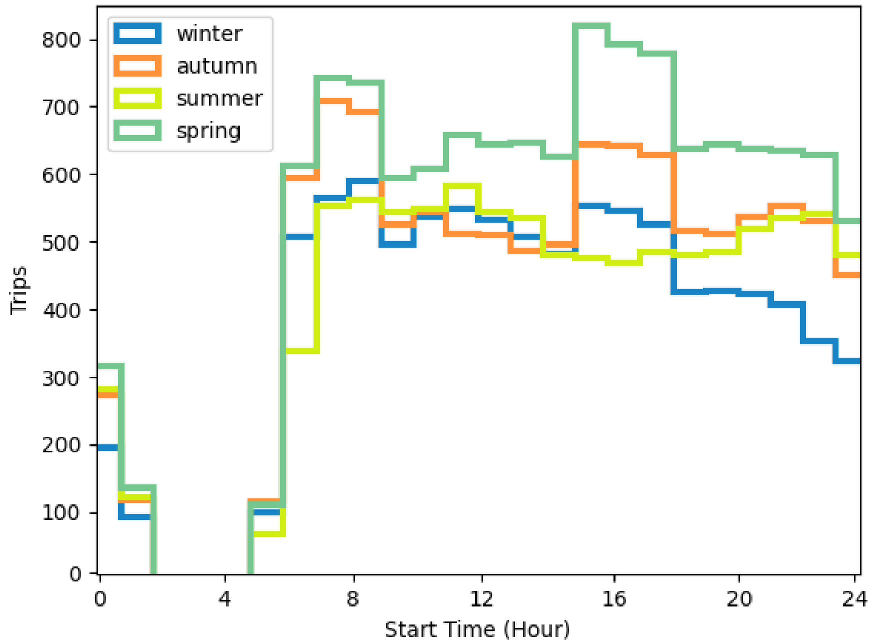


Figure 5.1: departure times line 3

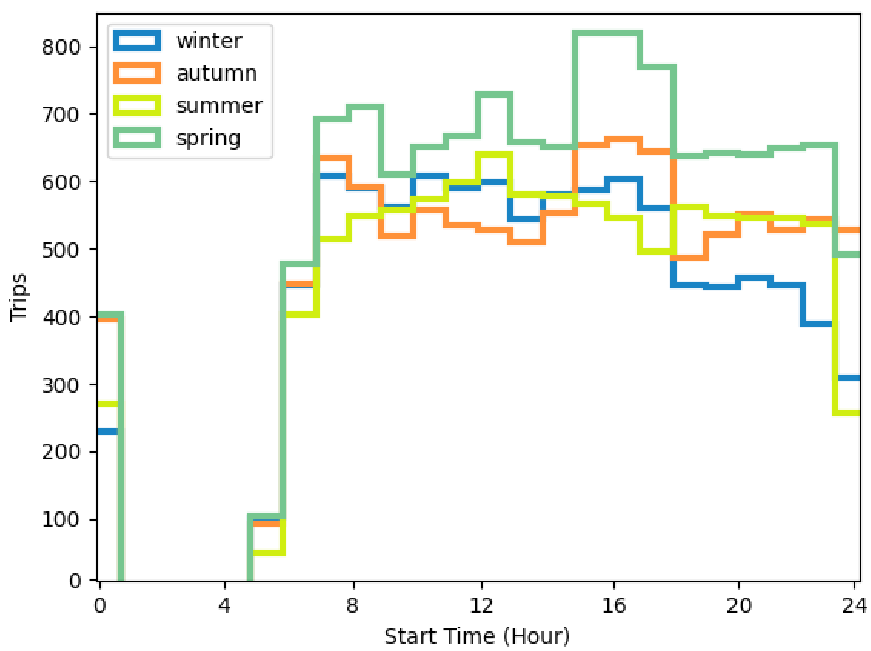


Figure 5.2: departure times line 7

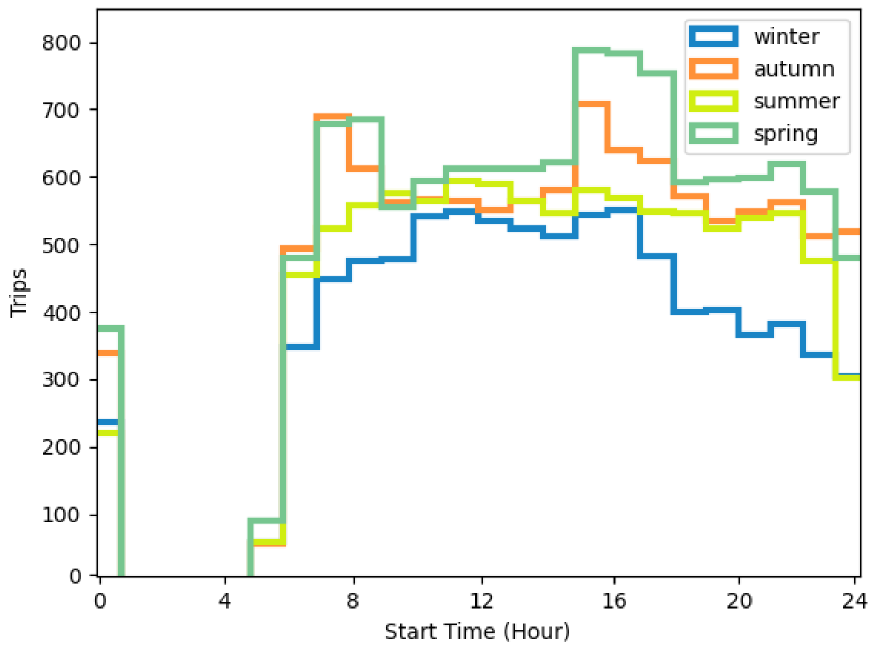


Figure 5.3: departure times line 8

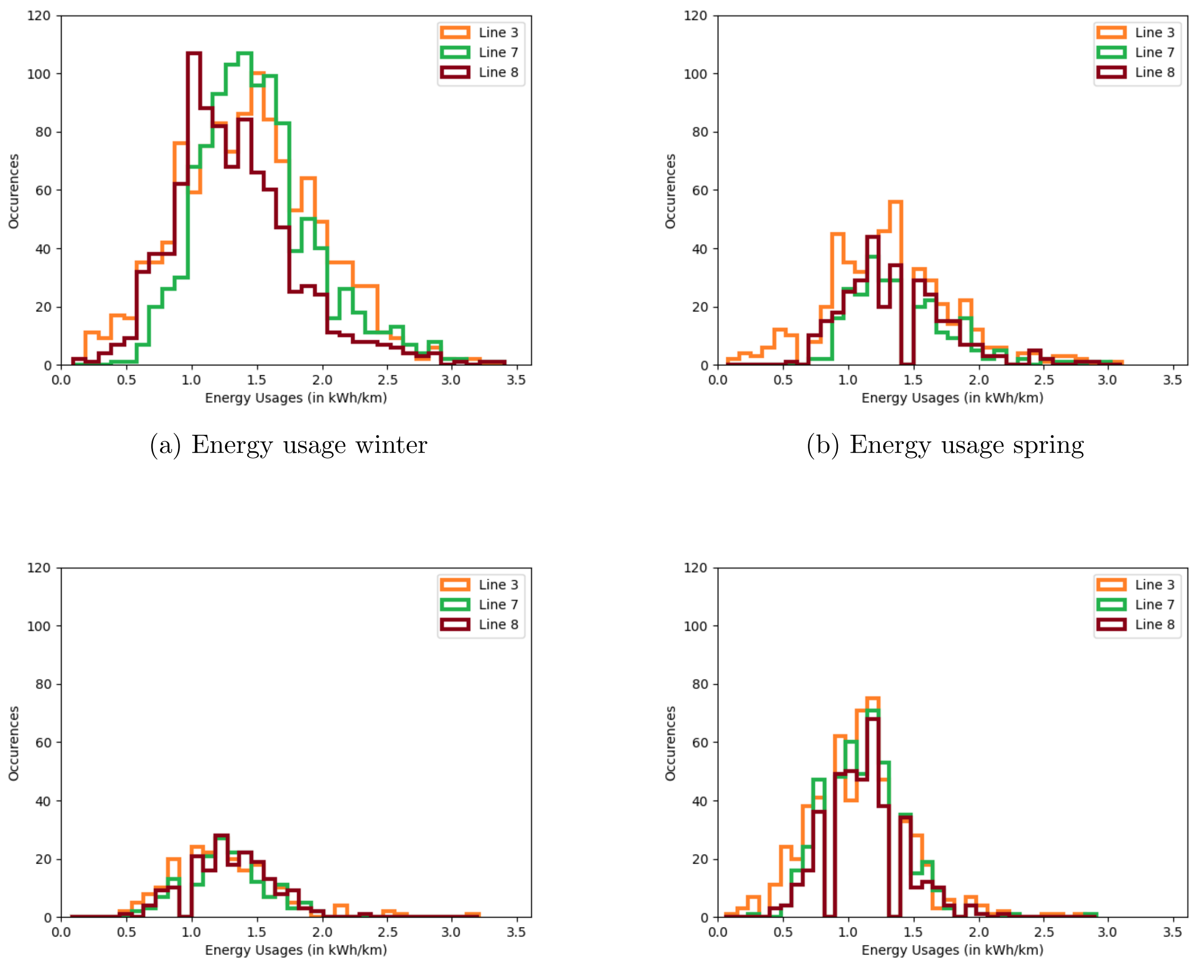
Besides the starting times of all trips, we are also interested in their deviation from the planned start time and the deviation between planned and realised trip duration. In Appendix A you can find the distributions of the departure and driving times of each bus line split into the proposed seven different time slots. In general, we can see that buses take just shy of the planned trip duration time to perform the trip. We also notice that buses generally depart at their planned departure time, meaning buses are generally speaking earlier at the end of their trip than planned. This could indicate that the real charging time could be, generally speaking, longer as the trips take less time than planned.

5.2 Electricity Usage

Besides the trips, we also have the electricity usage of the buses. The electricity usage is calculated between charging events. We use the SoC difference and the odometer difference to calculate the electricity usage per kilometre of each bus. We split this usage up for all three bus lines, as each route could have different characteristics, which could result in different average electricity usages. Table 5.3 shows the number of charging events per bus line and Figure 5.4 shows the distribution of the different battery efficiencies for each bus line. One odometer did not function properly, so we have electricity usage data from 34 buses instead of 35. Due to rounding applied to the acquired data, there are some bins with no entries, as the rounding puts them into an adjacent bin.

Bus line	3	7	8
Winter	934	1.054	1.203
Spring	308	263	485
Summer	184	168	205
Autumn	398	462	547

Table 5.3: Charging events per season



(a) Energy usage winter

(b) Energy usage spring

(c) Energy usage summer

(d) Energy usage autumn

Figure 5.4: Electricity usages per season

In each figure we observe three, sometimes rough, normal distributions. All three bus lines show roughly the same shape, which could indicate that the routes do not have special characteristics belonging solely to themselves. There are some efficiencies that have been left out as they are deemed unrepresentatively high. These efficiencies are worse than 5.0 kWh/km. The most common energy usage per kilometre seems to be around 1.3 kWh/km, for each season. The only real noticeable difference is the wider spread of efficiencies during the winter. This could be a result of the use of auxiliary systems, such as electrical heating, but we can not state this with 100% confidence.

Chapter 6

Other Datasets

Besides data from the bus operator, we also need data from other sources. The datasets from external parties are discussed in this section. In Section 6.1 we will take a look at the data from the DAM and in Section 6.2 we will take a closer look at the weather data.

6.1 Day-Ahead Market Prices

First up, we will take a look at the electricity prices from the years 2020-2022. Electricity price data is gathered from ENTSO-E (n.d.). We will start by taking a look at every year, followed by highlighting a single day. We finish this section off by looking at the three years altogether.

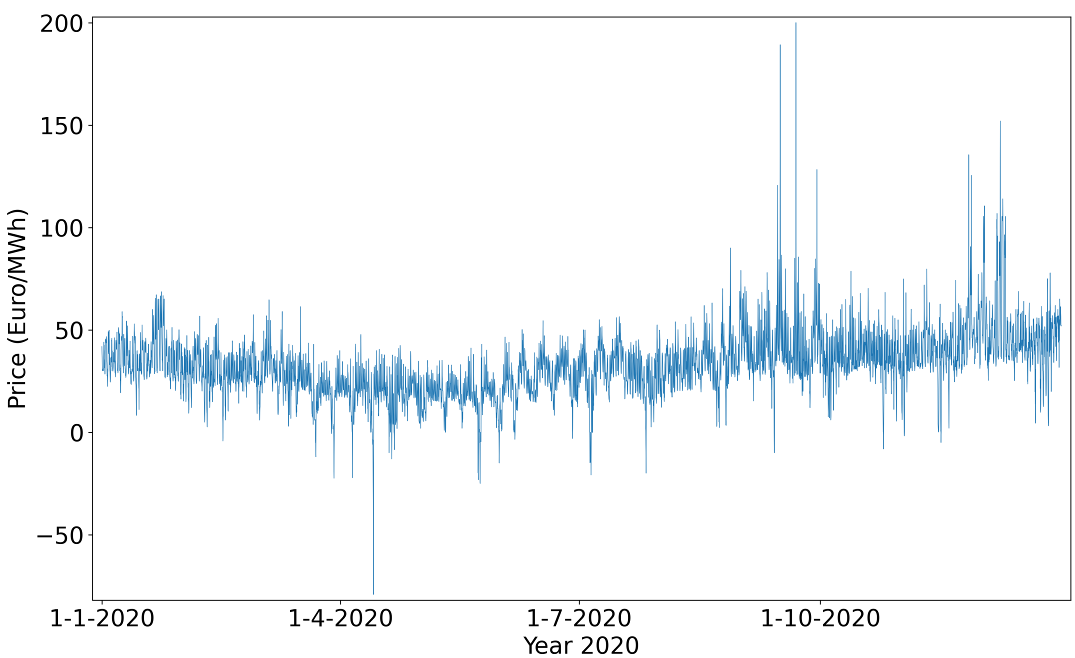


Figure 6.1: DAM 2020

Electricity prices start off relatively steady in the year 2020, see Figure 6.1. We see that in the early half of the year, there are some spikes downwards, indicating lower and even negative pricing. The second half of the year shows more signs of sporadic pricing increases, rather than decreases as seen in the first half of the year. The last thing to note is that the average pricing at the end of the year is slightly higher than at the start of the year.

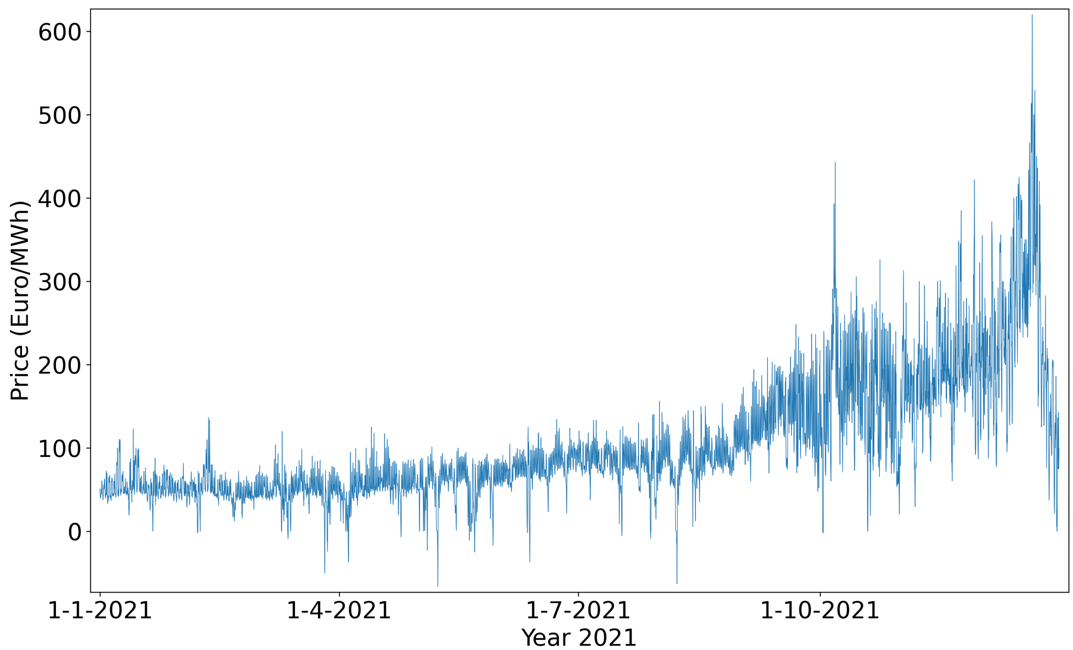


Figure 6.2: DAM 2021

In the year 2021 a steady increase in electricity pricing is noticeable, see Figure 6.2 and also notice the different scale of the y-axis when compared to Figure 6.1. The European Council (n.d.) explains the reason for this rise to be the dependency on the import of energy. As the prices of imported energy rose, likely due to the increasing demand after the COVID-19 pandemic, the prices for consumers also rose steadily.

Besides the general increase in electricity pricing, price spiking also occurred more often and became more extreme, especially in the positive numbers.

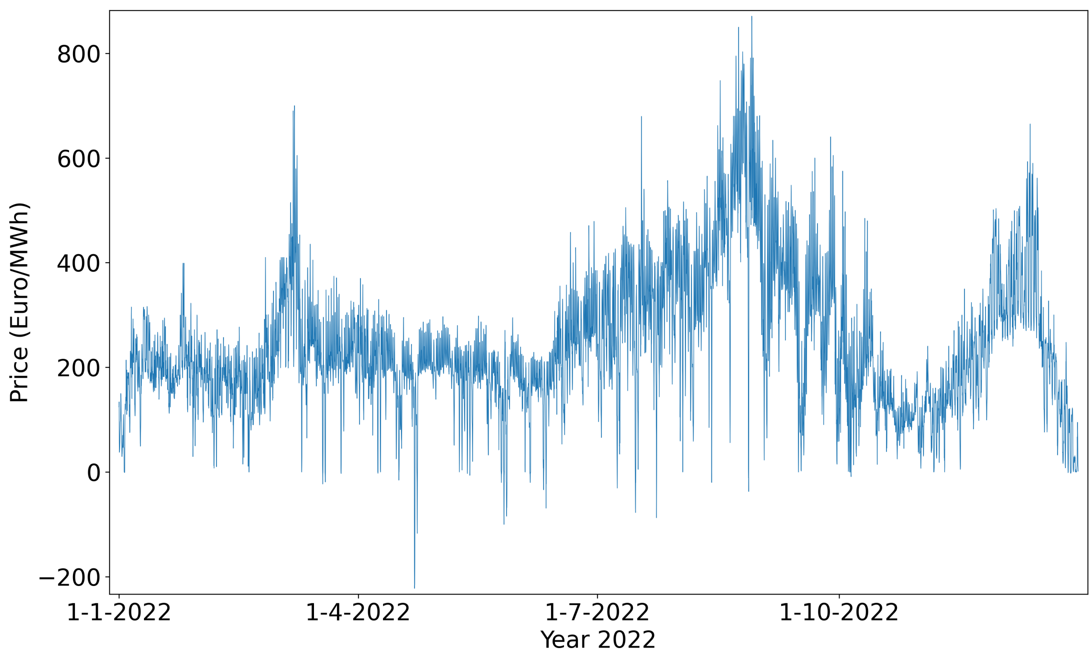


Figure 6.3: DAM 2022

In the year 2022, see Figure 6.3, prices further went up in comparison to the year 2021. The European Council (n.d.) says the reason for this further rise comes down to both the war in Ukraine and the heatwaves during the summer.

As Russia invaded Ukraine, the gas delivery from Russia to the EU became unstable. Both Russia and the EU suspended gas trades. This forced the EU to buy from other parties, which in turn raised their prices for gas. As the EU uses gas as a primary source for electricity generation, electricity prices were also raised.

Besides the war, the summer of 2022 was a hot one. In turn, many households and companies bought and/or turned on their cooling units, which draw a lot of power, thus increasing the electricity demand as well. These heatwaves also decreased the energy supply due to droughts and the consequent reduction in the supply of hydropower.

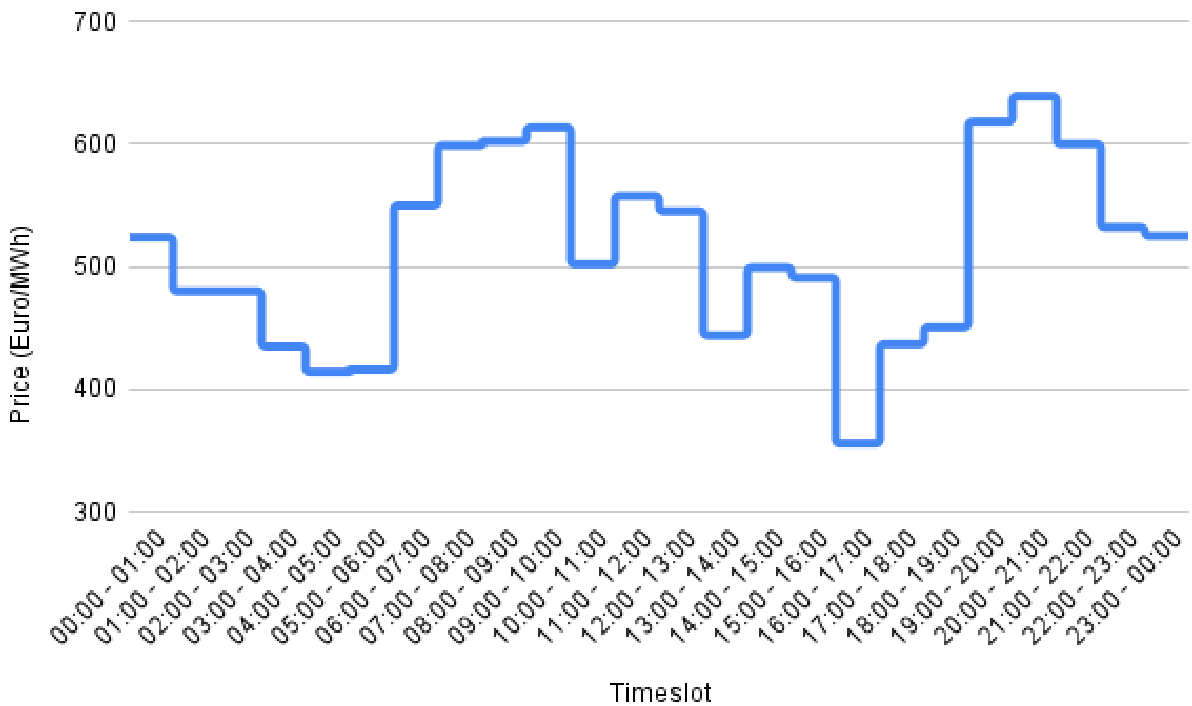


Figure 6.4: DAM price of 18-08-2022

To give a clearer view of these pricing changes, we will take a look at a single day, see Figure 6.4. Note that the y-axis goes from €300 to €700. For this instance we look at the pricing during Thursday the 18th of August, 2022. This is an example of a day in which cost savings are expected to be made, as the price fluctuates substantially between multiple hours. We can see that the cost for one MWh goes from €355 at 16:00 to €639 at 20:00. An interesting observation is the price dips at 10:00, 13:00 and 16:00. These prices are cheaper than the hours surrounding them, making them the perfect time to use electricity. Besides this, we see a lower price between 3:00 and 6:00 and price spikes after low price timeslots.

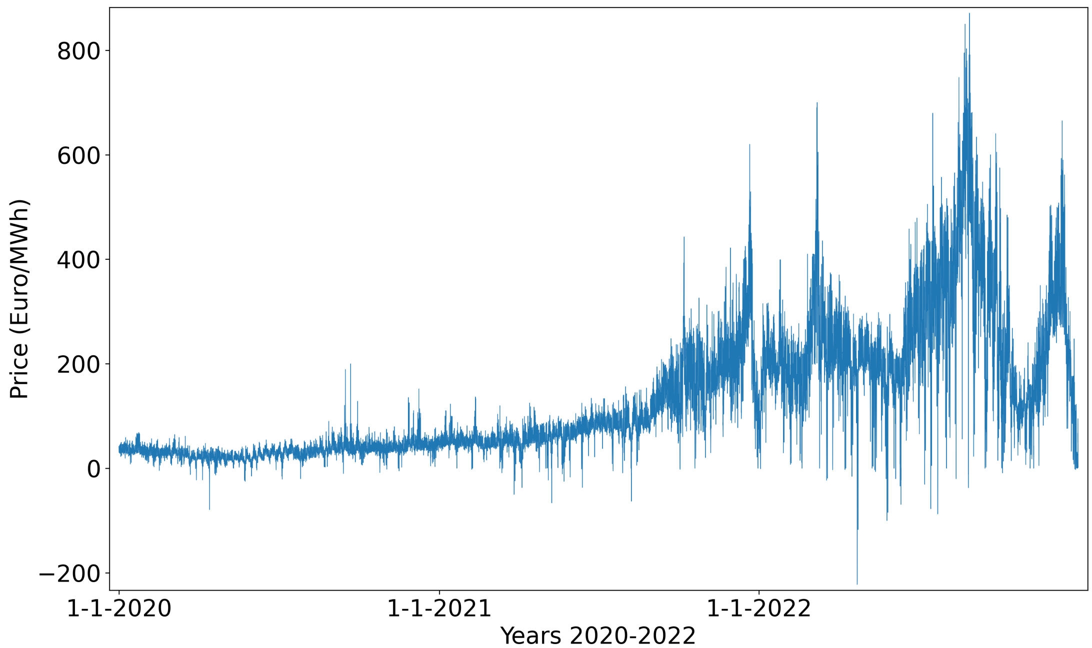


Figure 6.5: DAM 2020-2022

Finally, we will quickly look at the years 2020 to 2022 in one graph, see Figure 6.5. This graph perfectly shows the increase in the average electricity price and the increase of massive price spikes both upwards and downwards. It also shows the pricing spread becoming bigger. In the year 2020 the line fluctuation is rather small. If we look at the year 2021 we see that the price fluctuation already creates some bigger differences. From the end of 2021 onwards the prices vary much more during a short period of time, complimented with many more price spikes, making the price more and more uncertain.

6.2 Weather Statistics

The last used dataset is provided by the (KNMI). The dataset provided by the KNMI (n.d.) has data all the way back from the first of January 1901, but we will be focussing on the data from the year 2022. The decision was made to use the data from the station in De Bilt as this station is located very close to Utrecht (8 km away from the city centre) and it is the headquarters of the KNMI, which results in the data being homogenized. To see the data in a more detailed manner, take a look at Appendix B.

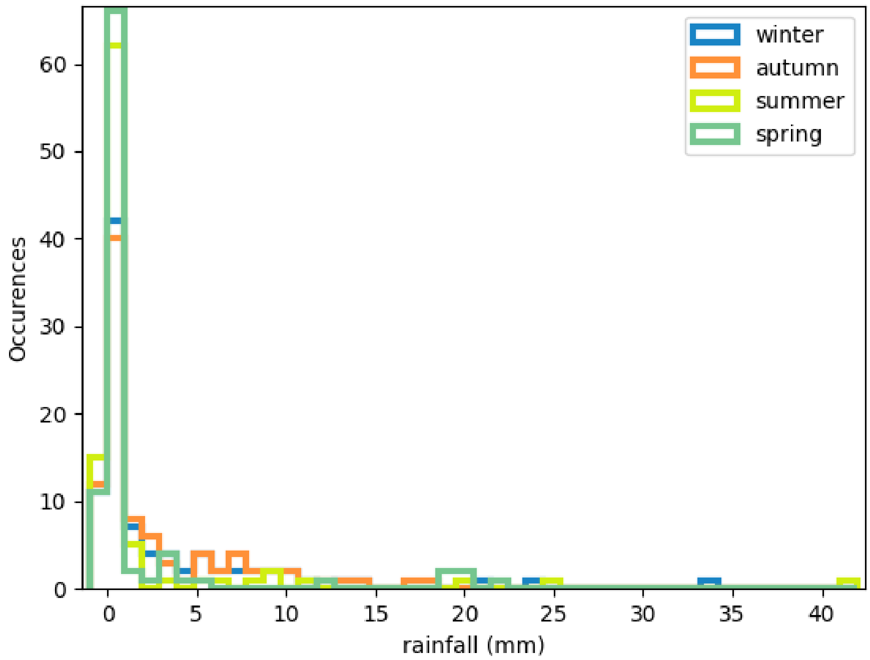


Figure 6.6: KNMI rain

We start with the measured rainfall, see Figure 6.6. We can see that about 50 days have a total rainfall of -1, according to the KNMI. They state that the measured rainfall on those days is less than 0.05mm and thus get classified as -1mm of rainfall. Besides that we can see there are a lot of days with a total rainfall amount between 0.05mm and 1mm. The more rainfall was measured the less often it occurred, which gives us a very left skewed distribution. The highest amount of rainfall on a single day is 42.8mm of rain. This happened on the 17th of August when heavy local rainfall occurred in the midst of a heatwave.

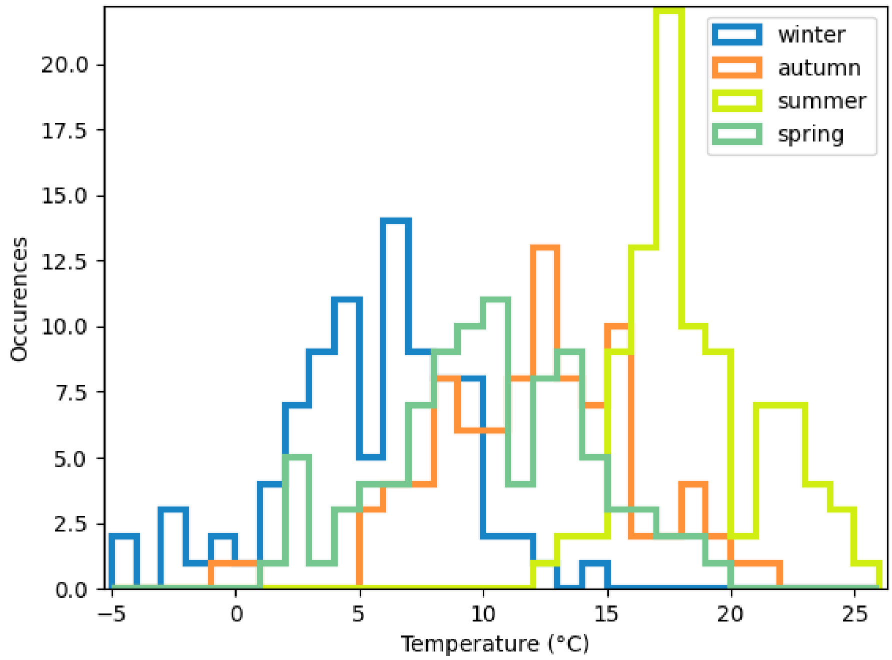


Figure 6.7: KNMI temp

Next we take a look at the average temperature. The average temperature data over the year 2022 shows a rough normal distribution for each season, with some small outliers. One example of this are the dips in the winter, spring and summer where at one specific temperature value the line is lower than both its neighbours. As these are averages of the whole day, the average temperature values happens to be just shy of this specific value, creating a dip in the graph.

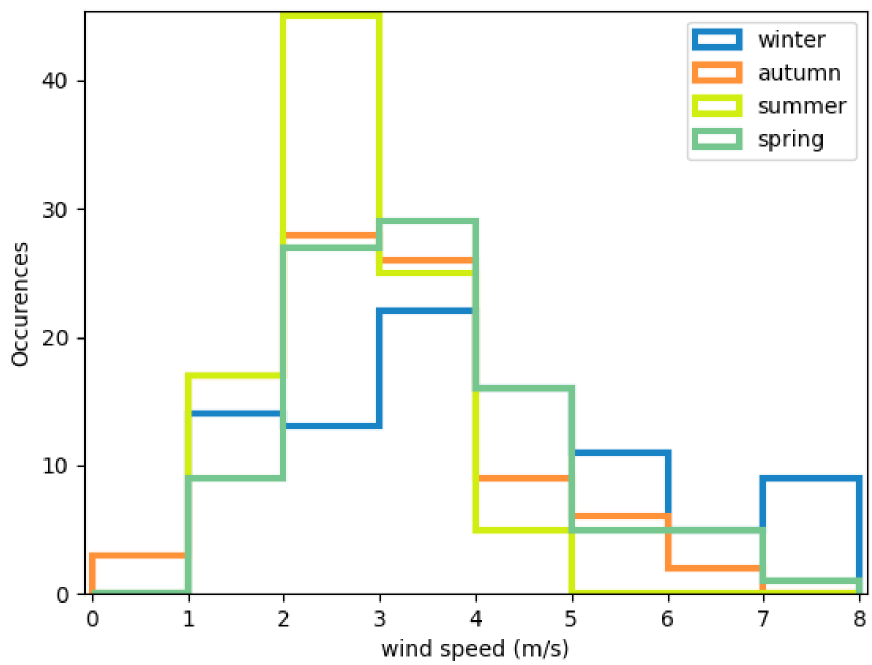


Figure 6.8: KNMI rain

The last data item we look at is the wind speed. We see that windstill days are very scarce, just as very windy days. Wind speeds of 8 meters per second up to 10.7 meters per second are categorised as a wind strength of 5 Beaufort. So it is very uncommon to see daily average wind strengths of 5 Beaufort and higher. We can observe that average wind speeds of 2 to 3 meters per second are the most common wind speeds. The is a small left-skewed distribution, but overall the distributions are rather evenly, with each season having a distinct peak.

Part III

Solution Approach & Implementation

In this part, we will take a look at the way the proposed research has been implemented. In Chapter 7 we will go through the standard charging manner, where we charge at full power whenever a bus is at a charging facility. This creates the baseline, which reflects the current way of charging. In Chapter 8 we will look at the implementation of the MILP. We will look at how it is built and what constraints are needed to create a ″smarter″ charging schedule, which will focus on reducing the charging costs. Finally, in Chapter 9 we discuss the validation of the charging schedule made by the MILP to see how robust and feasible it could be in the real world, where the trip durations and arrival/departure times are not fully compliant with the planned schedule and the electricity usage is variable instead of being static.

Chapter 7

Standard Model

The standard charging model is the simplest model of the three. We take the internal bus schedule from Qbuzz and walk through it. When we encounter a charging event, we will charge the bus at the maximum rate, according to the facility and the SoC of the bus. The costs are then calculated by multiplying the charged kWh with the price of a kWh according to the DAM pricing of that time.

By charging in this manner we are keeping the battery of a bus at the fullest possible SoC level. This allows for unexpected events, such as a problem at a charging station or unexpected delays, to be handled with more ease, as a bus likely has a high enough SoC to perform the next trip without reaching a SoC of 0%.

A side effect of this way of charging is that you charge whenever you are able to, without looking at the electricity prices. This can have the effect of using expensive electricity to charge a bus in one charging slot, whereas in the next slot the pricing might be much lower. Unfortunately, due to the earlier charging, the bus can still be rather full, which could result in less cheap charging and thus a higher electricity bill than necessary.

Other events, which have a distance value, are used to reduce the SoC level of a bus. This model uses a static SoC cost value per driven kilometre.

Finally, to make the model more representative, we apply a charger efficiency. As a charger does not convert 100% of the power used to the device being charged, we need to take into account the loss in this process as we pay for the power used but only a certain percentage gets put into the battery of a bus.

Chapter 8

MILP Model

The MILP will try to reduce the charging costs by taking the electricity pricing into account when charging a bus. In this chapter we will take a closer look at the steps involved in this process. We start with taking a look at the MILP formulation. After this, we will discuss the input data and we finish this chapter by shortly stating what we do with the output of the MILP model.

8.1 Formulation

In this section we will go over the MILP. We start with Table 8.1 which gives an overview of all the used sets, parameters and variables. We follow this up by going through each constraint used to create the model.

Set	Definition
B	Set of buses with index b
C	Set of charger locations with index c
$Events$	Set of all event timestamps in minutes. A timestamp is the time when a bus arrives or departs or it indicates a full hour
Parameter	
$avail_b$	Event timestamps when bus b is at a charger
$availSets_b$	Sets of event timestamps when bus b is at a charger. Each set s contains the timestamps present in a single charging window
Bat_{Cap}	Battery capacity in kWh
$c_{b,t}$	States which charger is in use by bus b at time t
$C_{c,b,t}$	States if bus b is at charger location c at timestamp t
Cap_c	Bus capacity per charger location c
CE	The charger efficiency
D_t	Indicates the amount of time between timestamp t and the next timestamp
E_b	Timestamp of each entry in $E_{b,t}$
$E_{b,t}$	Required energy of bus b at timestamp t to perform the trips until the next charging block in SoC
eps	Epsilon value
ET	The end time of the charging covered by the MILP
I	The amount of charge levels

$init_b$	The initial SoC value of bus b
$Lim_{c,i}$	The SoC value dictating the SoC limit of charging speed i for a bus per charger location c
M	Big M
m	The penalty multiplier which states the cost of each kWh below the desired lower limit
m_f	Cost of not fully charging a bus
MC	Minimum charge time in minutes
$Pow_{c,i}$	The charging speed limit per charger location c for charging level i
Pr_t	Electricity price in $Euros/kWh$ at event t
PT	The SoC below which a penalty is applied
$Starts_b$	The timestamps of all events where a charging window for bus b starts
W_b	Timestamps when bus b leaves a charger and we want to check for a full battery
Variable	
$D_{b,t,i}$ (continuous)	The amount of minutes used for charging by bus b at timestamp t at charging level i
$F_{b,t}$ (binary)	Indicates whether the battery of bus b is full at time t
$P_{b,t,i}$ (continuous)	The charging power of bus b at timestamp t at charging level i
$PEN_{b,t}$ (continuous)	The amount of penalty points of bus b at timestamp t
PEN_F_b (binary)	Indicates that bus b is not fully charged during a day
$S_{b,t}$ (binary)	Indicates whether the starting moment of a charge session of bus b is at timestamp t
$SoC_{b,t}$ (continuous)	The SoC of bus b at timestamp t
$SoC\_P\_D_{b,t}$ (continuous)	Abbreviation of the following formula: $X_{b,t} * SoC_{b,t} + P_{b,t,0} * D_{b,t,0} * CE$
$U_{b,t}$ (binary)	Binary product of $X_{b,t}$ and $X_{b,t-1}$
$V_{b,t,i}$ (binary)	States if charging level i is unlocked
$X_{b,t}$ (binary)	States if bus b is charging at timestamp t
$Z_{b,t,i}$ (binary)	States if charging level i is locked

Table 8.1: Definitions of sets, parameters and variables of the MILP model

The idea of the MILP is to minimize the cost of charging electric buses. To achieve this we will start with an objective function stating the cost of charging, which we want to minimize. We calculate the cost of charging using the charging duration times the charging speed, which we then multiply by the battery capacity to calculate the amount of kW charged. Lastly to get the cost, we multiply the kW charged by the cost of a single kW.

$$\min \quad \sum_{t \in Events} \sum_{b \in B} \sum_{i=0}^{I} P_{b,t,i} * D_{b,t,i} * Bat_{Cap} * Pr_t \tag{8.1}$$

Note that we immediately create a product of two variables, resulting in an equation which is not linear. We will address this quadratic problem at a later point.

For this objective function to work we need to set the initial SoC of the bus and update the SoC at each event (timestamp) according to a charge or discharge of the battery. Set the initial SoC value of the buses

$$SoC_{b,0} = init_b \qquad \forall b \in B \tag{8.2}$$

and update the $SoC_{b,t}$ each t in $Events$ depending on if the bus departs or is possibly charging.

$$SoC_{b,t+1} = \begin{cases} SoC_{b,t} - E_{b,t} & \forall t \in E_b, \forall b \in B \\ SoC_{b,t} + \sum_{i=0}^{I} P_{b,t,i} * D_{b,t,i} * CE & \text{if } t \notin E_b, \forall t \in Events, \forall b \in B \end{cases} \tag{8.3}$$

We now have the problem that at each point, the charge can go from 0% to 100% in a single step, as the charging power and time are not limited. We will start by limiting the charging time of the bus at each timestamp. This makes sure the amount of time the bus is able to charge is at most the time between two consecutive event timestamps. An event happens when a bus arrives at a charger, leaves a charger or it is a full hour, meaning there possible is a change in electricity price.

$$\sum_{i=0}^{I} D_{b,t,i} \leq D_t \qquad \forall t \in Events, \forall b \in B \tag{8.4}$$

And now we limit the power with which the bus can charge. Note that we have multiple charging locations, so we have multiple limits as the limit depends on the charger in use, see Table 3.1 and Figure 3.2. Because some chargers do not charge to 100%, we will also have to limit the maximum charge depending on the charger being used.

$$P_{b,t,i} \leq Pow_{c_{b,t},i} \qquad \forall t \in avail_b, \forall b \in B, \forall i \in I \tag{8.5}$$

$$SoC_{b,t+1} \leq Lim_{c_{b,t},2} \qquad \forall t \in avail_b, \forall b \in B \tag{8.6}$$

It was previously noted that a battery lifespan is increased if it is not fully discharged. For this, we create a threshold which we do not want the battery to be below, but we are lenient with this. We will allow the battery to dip below this value, at a certain cost. This allows the battery charge to be below this threshold, but the cost savings created with charging later must be large for this to be used. To model this we give a penalty for the amount of SoC below this threshold. We only set this penalty at timestamps when a bus leaves a charger, as we remove the total amount of SoC used before returning to a charger at this timestamp and thus calculate with the lowest SoC the battery can be, as it will only become higher or stay the same when located at a charger.

$$PEN_{b,t} \geq PT - (SoC_{b,t} - E_{b,t}) \qquad \forall t \in E_b, \forall b \in B \tag{8.7}$$

To add this penalty cost to the MILP, we alter the objective function (as seen in 8.1) to include the penalty points multiplied by the cost of being below the soft SoC threshold.

$$\min \quad \sum_{b \in B} \sum_{t \in E_b} PEN_{b,t} * m + \sum_{t \in Events} \sum_{i=0}^{I} P_{b,t,i} * D_{b,t,i} * Bat_{Cap} * Pr_t \tag{8.8}$$

Due to warranties from the manufacturer, we add the requirement that a bus must be fully charged at least once every day. As we will be saving the outcome between 1 PM day 1 and 1 PM day 2, which will be discussed in Section 8.3, we will enforce the battery to be fully charged once within this time-frame. We enforce this using the following constraints:

$$F_{b,t} \leq SoC_{b,t} \qquad \forall t \in W_b, \forall b \in B \tag{8.9}$$

$$\sum_{t \in W_b} F_{b,t} \geq 1 \qquad \forall b \in B \tag{8.10}$$

We want to make sure that a bus can only charge when it is occupying a charger. To do this we will set the amount of charging time to zero if the bus is not occupying a charger. For this we alter constraint 8.4 to constraint 8.11.

$$\sum_{i=0}^{I} D_{b,t,i} \leq D_t * X_{b,t} \qquad \forall t \in Events, \forall b \in B \tag{8.11}$$

When a bus does occupy a charger we want it to charge for at least for a certain amount of time (Minimum Charge time) to prevent charges which are so small that they will not be worth the trouble of connecting and disconnecting to the charger.

$$\sum_{t \in s} \sum_{i=0}^{I} D_{b,t,i} \geq MC * \sum_{t \in s} S_{b,t} \qquad \forall s \in availSets_b, \forall b \in B \tag{8.12}$$

For constraint 8.12 to work we need to prevent the bus from occupying a charger when it is not at a charging location, as this would not be physically possible.

$$X_{b,t} = 0 \qquad \text{if } t \notin avail_b, \forall t \in Events, \forall b \in B \tag{8.13}$$

In combination with constraint 8.11, we are now able to control if a bus can charge or not when located at a charger. Furthermore, we want the bus to charge only once during its availability window. For this to work we also need to keep track of when a bus starts charging ($S_{b,t}$) and when it is charging ($X_{b,t}$). For this we need the following constraints.

$$S_{b,t} = X_{b,t} \qquad \forall t \in Starts_b, \forall b \in B \tag{8.14}$$

$$S_{b,t} = X_{b,t} - U_{b,t} \qquad \text{if } t \notin Starts_b, \forall t \in avail_b, \forall b \in B \tag{8.15}$$

$$U_{b,t} \leq X_{b,t-1} \qquad \text{if } t \notin Starts_b, \forall t \in avail_b, \forall b \in B \tag{8.16}$$

$$U_{b,t} \leq X_{b,t} \qquad \text{if } t \notin Starts_b, \forall t \in avail_b, \forall b \in B \tag{8.17}$$

$$U_{b,t} \geq X_{b,t} + X_{b,t-1} - 1 \qquad \text{if } t \notin Starts_b, \forall t \in avail_b, \forall b \in B \tag{8.18}$$

With these constraints we indicate when a bus starts a charging session, using $S_{b,t}$, which is calculated using the values of $X_{b,t}$ and $X_{b,t-1}$ to create the binary variable $U_{b,t}$, as inspired by Abdelwahed et al. (2020). What this means is that $S_{b,t} = 1$ when $X_{b,t} = 1$ and $X_{b,t-1} = 0$, otherwise $S_{b,t} = 0$ and we do not start a charging moment at this event. Constraints 8.14 - 8.18 make sure the model adheres to this rule. By doing this we can allow the bus to start charging at most once, and thus connect the bus to the charger at most once during a charging opportunity window. This is done to prevent the driver from doing more actions than necessary. Constraint 8.19 enforces this action.

$$\sum_{t\in s} S_{b,t} \leq 1 \qquad \forall s \in availSets_b, \forall b \in B \tag{8.19}$$

Now that we have the ability to turn the charging on and off we will change constraint 8.6, as there is a problem when the bus has a higher SoC at arrival than the charger limit allows. To make sure this does not break the program, we only enforce the limit when we are charging the bus, see constraint 8.20.

$$X_{b,t} * SoC_{b,t+1} \leq X_{b,t} * Lim_{c_{b,t},2} \qquad \forall t \in avail_b, \forall b \in B \tag{8.20}$$

Each battery part of this charging model is dependent on the part before it, as the battery needs to have a certain amount of SoC before the new maximum charge speed is able to be used, see Table 3.1 and Figure 3.2. To make sure the charging occurs in the right block, we need to lock and unlock each part according to the SoC level of the battery. We start by introducing the constraint which will unlock the next charging part. For this we use $V_{b,t,i}$. To make the constraint shorter we will write $X_{b,t} * SoC_{b,t} + P_{b,t,0} * D_{b,t,0} * CE$ as $SoC\_P\_D_{b,t}$.

We first need to set the $V_{b,t,i}$ value before we can use it to unlock the next charging parts. We unlock the next part if the previous part is equal to the maximum SoC it can become. $V_{b,t,1}$ unlocks the second part and $V_{b,t,2}$ unlocks the third part by becoming 1.

$$V_{b,t,1} \geq \lfloor SoC\_P\_D_{b,t} / Lim_{c_{b,t},0} \rfloor \qquad \forall t \in s, \forall s \in availSets_b, \forall b \in B \tag{8.21}$$

$$V_{b,t,2} \geq \lfloor (SoC\_P\_D_{b,t} + P_{b,t,1} * D_{b,t,1} * CE) / Lim_{c_{b,t},1} \rfloor \qquad \forall t \in s, \forall s \in availSets_b, \forall b \in B \tag{8.22}$$

Now that we have values indicating if the next part is (un)locked we can use this to prevent charging in locked parts using the following constraint

$$D_{b,t,i} \leq D_t * V_{b,t,i} \qquad \forall t \in Events, \forall i \in \{1,2\}, \forall b \in B \tag{8.23}$$

Lastly, we need to make sure that each charging part only charges the battery up to the given limit, thus making sure we do not charge more with a certain speed than allowed. For this we use the Z variable. $Z_{t,0}$ indicates if the first part is locked and $Z_{t,1}$ indicates if the second part is locked by becoming 1. When we unlock the second part using $V_{b,t,1}$ we know that the first part is locked, as the right hand side in constraint 8.24 becomes 1, so must the left hand side be.

$$Z_{b,t,i} \geq V_{b,t,i+1} \qquad \forall i \in \{0,1\}, \forall t \in s, \forall s \in availSets_b, \forall b \in B \tag{8.24}$$

We can now dictate how much SoC the first and second part are able to charge, depending on how much charge there already is in the battery and if we are allowed to use the specific battery part. If the part is locked, the right hand side becomes 0, resulting in no charging happening for that part.

$$P_{b,t,0} * D_{b,t,0} * CE \leq (1 - Z_{b,t,0}) * (Lim_{c_{b,t},0} - SoC_{b,t}) \qquad \forall t \in s, \forall s \in availSets_b, \forall b \in B \tag{8.25}$$

$$P_{b,t,1} * D_{b,t,1} * CE \leq (1 - Z_{b,t,1}) * (Lim_{c_{b,t},1} - SoC\_P\_D_{b,t}) \qquad \forall t \in s, \forall s \in availSets_b, \forall b \in B \tag{8.26}$$

Using this MILP we notice that sometimes the bus is not able to fully charge its battery during a day. For this we introduce a variable which allows the bus to not fully charge, but at a cost m_f. For this to work, constraints 8.8 and 8.10 need to be altered. This results in constraints 8.27 and 8.28.

$$\min \quad \sum_{b \in B} \sum_{t \in E_b} PEN_{b,t} * m + PEN\_F_b * m_f + \sum_{t \in Events} \sum_{i=0}^{I} P_{b,t,i} * D_{b,t,i} * Bat_{Cap} * Pr_t \tag{8.27}$$

$$\sum_{t \in W_b} F_{b,t} + PEN\_F_b \geq 1 \qquad \forall b \in B \tag{8.28}$$

Finally, as each charging location has a certain number of chargers, we need to make sure that a charger is not used by two or more buses at the same time. For this we use the amount of chargeable time between two events multiplied by the total amount of chargers to calculate how many minutes are able to be used for charging per charging location. For example we have two chargers and five minutes between two events. Let's say there are three buses wanting to charge, then they will have to divide the ten chargeable minutes over the three of them, whilst also adhering to the constraint that a single bus can not charge for more than the five minutes between the events. The amount of time it takes to disconnect a bus and connect a different bus is already processed in their availability window, so we will not be taking extra steps to manage the switching of buses at a charger.

$$\sum_{b=0}^{B} \sum_{i=0}^{I} C_{c,b,t} * D_{b,t,i} \leq Cap_c * D_t \qquad \forall c \in C, \forall t \in Events \tag{8.29}$$

The MILP will be solved using Gurobi, which will translate the quadratic constraints and quadratic objective terms into linearly separable constraints and objective terms. We chose to let Gurobi translate these quadratic problems, as it will do this in a very efficient manner.

8.2 Input Data

In this section we will quickly highlight some of the input data used in the MILP.

The values E_b, $E_{b,t}$ and $avail_b$ are made by reading the internal bus schedule and extracting the needed electricity and charging events for each bus trip in the schedule. Values E_b state the times (in minutes) when a certain level of SoC is used by bus b. Values $E_{b,t}$ state the amount of SoC drained from the battery by bus b at time t. The values in $avail_b$ state all the timestamps when bus b is at a charger, whereas $availSets_b$ are sets of the timestamps contained in a charging window for bus b. Each set are the timestamps captured in a single charging window. Or in other words: each set are the timestamps between the time a bus arrives (inclusive) and the bus departs (exclusive) from a charger.

As each MILP run will get processed individually, starting from 1 PM on day x to 6 AM on day x+2, we will be using the real DAM prices. Dam prices for the day x+1 get published at 1 PM on day x (exactly at the start of the MILP run), meaning only the last 6 hours have an unknown value. For this research we chose to also use the real DAM pricing for these values as the prices, generally speaking, are more stable during these hours.

The last input data we will highlight is the *Events* set. This set contains all the times (in minutes) in ascending order when an event happens. For this research an event is an arrival of a bus at a charger location, a departure of a bus from a charger location and the time when the electricity price changes (every full hour). These moments are the only moments when a change in charging of buses is interesting, as the price of the electricity may change or a new bus needs to be charged at a location where the capacity is already full and one of the buses will have to make room for the arriving bus. This also helps to reduce the total amount of variables used in the MILP compared to having fixed time steps of one minute,

8.3 Output

We know that a single MILP run will start at 1 PM on day x (780 min) and run to 6 AM on day x+2 (3240 min). Afterwards, the charging choices between 1 PM day x and 1 PM day x+1 are saved as the charging schedule. These values will not change when the new DAM prices are published, as they lay in the past.

Chapter 9

Validation Model

Now that we are able to create a more cost-effective charging schedule using the MILP, we want to test how robust it is. Is the created charging schedule a utopia, which is never reachable or is the new charging schedule achievable? We will test how feasible the new schedule is using simulation. For this, we take the original bus schedule and alter the arrival and departure times using data from the realised bus schedule. We alter these using the stochastic trip times and stochastic departure punctuality. Besides altering the times of the bus schedule, we will also make the electricity usage variable, which results in both more and less efficient electricity usages than the previously used static value. The simulation works in the following manner:

We simulate the bus schedule for a whole year. The original arrival and departure times of a trip in the schedule are changed. How we do this is discussed in Section 9.1. These new values could create larger charging windows than originally planned, giving us more time to recharge, but they can also become smaller. Possibly so small that we do not allow a charging event to be planned. The minimal time between arriving and departing at a charger has to be five minutes in order to be seen as a possible charging event. This could result in buses not getting the needed recharge, resulting in a lower SoC than expected.

Besides the possibly shortened or even omitted planned recharging events, the buses also have a stochastic battery consumption rate, see Section 9.2. This means that the used electricity per kilometre can be higher or lower than what was used to create the charging schedule. To accommodate for the difference in expected and realised SoC, we allow the buses to greedily recharge when their SoC is lower than expected, up to the expected SoC. This way of handling lower SoC values is chosen to make the operations easier, instead of trying to optimise the recharging of the missed charge, which could also fail due to the stochastic nature of the simulation. In other words, the missing charge is recharged as soon as possible, allowing us to follow the created charging schedule more accurately from there on forward.

If a bus's SoC would go below zero when performing the next scheduled trip, the vehicle task stops at that point and the bus arrives at the charger at the time it was supposed to arrive according to the schedule. We save this event as a bus running out of battery. We will use this to see how robust the proposed charging schedule is.

Before we start creating the new schedule and variable electricity usages, we will first look for correlations between both trip times and parameters in the KNMI dataset and between electricity usages and parameters in the KNMI dataset. We do this check in order to use the correct input for our simulation. We will use the following data for the KNMI dataset: average daily wind speed, average daily temperature and daily total rainfall.

9.1 Trip Times

For our stochastic trip time values, the time between starting and finishing a trip, we want to find out if there are correlations between the realised trip times and the weather parameters at those moments. In Figure 9.1 we see that there are no strong correlations between trip durations and the proposed parameters. With this we can conclude that for the stochastic trip durations we do not have to take these proposed parameters into account and can solely use the distributions of previously achieved trip times. Note that the deadhead trips of a bus still use a static duration, as we do not have previously achieved durations of these movements.

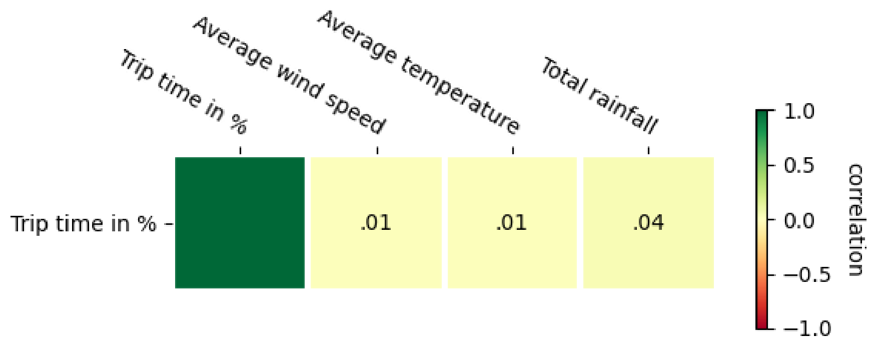


Figure 9.1: Pearson's correlation coefficients between trip duration and weather variables

9.2 Electricity Consumption

For our stochastic electricity consumption values we want to find out if there are any correlations between the archived electricity consumption rates and the proposed weather parameters. We also check for correlations between the electricity usage and the trip time in percentage of the planned trip time. In Figure 9.2 we see that there are no strong correlations between electricity consumption and the proposed parameters, so we do not have to take these correlations into account.

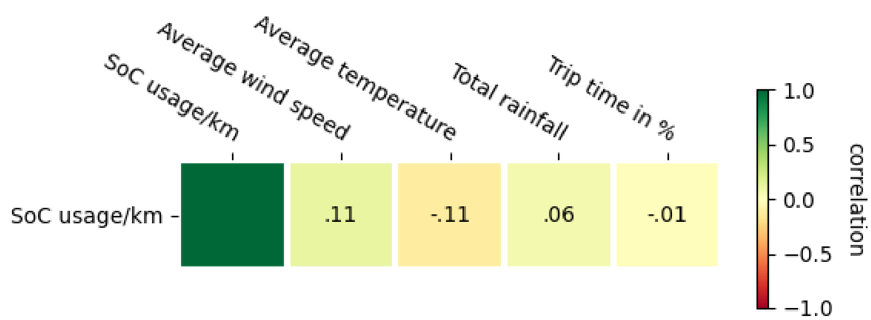


Figure 9.2: Pearson's correlation coefficients between electricity consumption and weather variables

To make the electricity usage more diverse we use Monte Carlo Simulation to simulate the electricity consumption. We start with the baseline electricity consumption, which is the overall electricity consumption rate for the year 2022. We then use Monte Carlo simulation to create different electricity consumption rates using the parameters which describe the moment we are simulating. These parameters are average temperature, average wind speed, total rainfall, current time, day of the week and lastly the season. Even though no correlations were found, we will also be using the average influence of these factors in order to have a more representable electricity usage. Each of the ten runs originally has the same electricity consumption variation, as the input variables for each run are the same. We apply a uniform distribution on each consumption variation value, to create different electricity consumption rates. The average consumption rate variation over all these runs is then added to the baseline efficiency to create a new electricity usage rate. This simulation is done for each trip in the schedule, which leads to each trip having its own stochastic electricity usage.

In table 9.1 an overview of the ranges of electricity rate consumption variation per variable are given. The values are in percentage of deviation from the average electricity consumption. This shows the range of effect each variable has on the electricity consumption rate.

Parameter	max consumption decrease	max consumption increase
Temperature	-9%	12%
Wind speed	-8%	28%
Rainfall	-7%	33%
Time	-16%	10%
Day of the week	-2%	2%
season	-7%	11%

Table 9.1: Variable Effects (in percentage deviation from the average consumption)

Part IV

Results & Conclusion

Chapter 10

Results & Discussion

10.1 Results

Model	Cost	Savings compared to SM (in percentage)
Standard Model (SM)	[redacted]	-
MILP Model (MM)	[redacted]	31.4%
Validation Model (VM)	[redacted]	23.9%

Table 10.1: Results electricity prices 2020

We start with the results using the DAM prices of the year 2020. Remember from Section 6.1 that these prices are, generally speaking, relatively steady and low when compared to the DAM prices during the years 2021 and 2022. We see that using the MM we are theoretically able to reduce the costs by 31.4% when compared to the SM. If we look at the VM, we see that the expected real-world savings are 'only' 23.9%.

Model	Cost	Savings compared to SM (in percentage)
Standard Model (SM)	[redacted]	-
MILP Model (MM)	[redacted]	28.8%
Validation Model (VM)	[redacted]	22.8%

Table 10.2: Results electricity prices 2021

Using the prices of the DAM in 2021, which are generally speaking more unstable and higher than the prices in 2020, we see the following results. Using the MM we are theoretically able to reduce the costs by 28.8% when compared to the SM. If we look at the VM, we see that the expected real-world savings are 'only' 22.8%.

Model	Cost	Savings compared to SM (in percentage)
Standard Model (SM)	[redacted]	-
MILP Model (MM)	[redacted]	28.9%
Validation Model (VM)	[redacted]	22.0%

Table 10.3: Results electricity prices 2022

Finally, using the DAM prices of the year 2022, which are generally speaking even more unstable and higher, the MM is able to theoretically reduce the cost by 28.9% when compared to the SM. If we look at the VM, we see that the expected real-world savings are 'only' 22.0%.

10.2 Discussion

10.2.1 Interpretation

Looking at the bigger picture, we see that on average the MILP model can reduce the recharging costs, compared to the standard charging, by 29.7% over a whole year. Note that both these models are deterministic and that the savings are only theoretical. In reality the buses do not drive exactly at the planned times and the electricity consumption rates are not static. What we do see from these results is that there is, supposedly, a large cost reduction to be found.

Comparing the results of each year, we see that when the electricity prices become more unstable, as seen in Section 6.1, the cost savings seem to be lower. There are multiple possible reasons for this behaviour. A possible reason for this trend is the DAM pricing. The prices at the times when buses need to be recharged, instead of having the ability to do so but not needing it, could have risen more than the prices at other times. As the buses need to be recharged during those times, we can not alter the charging schedule and shift them towards cheaper times, as this could result in buses running out of battery.

For this case study we are more interested in the expected real-world savings, as these are cost savings which are expected to be feasible using the given bus schedule. On average the expected feasible cost reduction is 22.9% over a whole year. As the validation model uses stochastic trip times and electricity consumption rates, the results from this model show the expected charging costs for the planned bus schedule. This is more valuable information for the PTO as they do not work theoretically, but they have real-world costs.

Due to the stochastic nature of the validation model, the buses might miss a planned charging event and/or use more electricity than planned. This results in some buses running out of battery. This is unwanted behaviour as a bus with zero SoC needs to be towed to a charger and a replacement bus needs to take over the planned vehicle task. This problem shows itself when running the schedule, which will need to be solved by the PTO during the day. Assigning different buses to take over a vehicle task from another bus already happens in practice as some buses are at risk of running out of battery, so this is no new phenomenon for the PTO. On average 4.33 buses are at risk of running out of battery each day in the validation model. To get some perspective on this number, we take a look at the realised bus schedule and see that the PTO switched 9.31 buses on average each day during the year 2022. This value is much higher than the 4.33 given by the validation model. Do note that we do not know the reason why the PTO switched buses on the vehicle trip. It could be to prevent buses from running out of battery, but it could also have a different reason, which is unknown to us.

10.2.2 Limitations

This research also has some limitations. The first limitation is the DAM pricing in the MILP model. In Section 8.2 we state that we use the real-world DAM pricing for all the hours, whereas in each MILP run the prices for the last six hours are supposed to be unknown, as the DAM pricing for these six hours is published at 1 PM the next day. To not overcomplicate this research, we chose to use the real values for these hours. Besides this, the nature of the MILP model tends to reduce this limitation. As each day the buses need to be fully charged, each bus is fully charged before 1 PM on day x+1. The data for the last six hours in the MILP model will therefore have, presumably, little effect on the overall cost savings.

Another limitation is the stochastic electricity consumption rate in the validation model. We use daily weather values, whereas during real operations these values are not static for a single hour, let alone for a whole day. At hour x the wind could be non-existent, whereas at hour x+3 there might be a storm coming. This could result in greater differences in electricity consumption rates, whereas the ones we use are more steady during a single day. Small changes in these values are already handled by the use of the Monte Carlo algorithm, but greater changes in the weather variables are out of the reach of the Monte Carlo algorithm.

Besides the cost of the electricity itself, there are other costs for the PTO regarding the electricity, such as the contract costs which are linked to the maximum throughput and the cost for the connection. The created charging schedule does not take notice of these costs. The presented charging schedule could be manually optimized for a small amount. For example when the schedule states 5 minutes of charging at a rate of 100 kW, but there are 10 minutes available. We could change this to 10 minutes of charging at 50 kW. This leads us to reduce the peak power usage and in turn lower the contract costs. However, we can only do this manual adjustment locally and thus other moments which can not be spread out will keep the contract costs high.

The last limitation we will state is the used bus schedule data, which was provided by the PTO. In this schedule there were some trips which were not registered correctly, leading us to not use them, see Section 5.1. This means that we are missing some bus trips and that the cost over a whole year will be more than our stated costs.

Chapter 11

Conclusion

11.1 Summary

In the first part of this thesis we stated the goal of this thesis. We wanted to research if the scheduling of the charging events and charging quantities using DAM information leads to a difference in electricity costs compared to the initially scheduled charging moments and quantities. We developed three models to see if this can make a difference. We created a baseline model, which charges whenever a bus is at a charger, at the maximum power. We then made a MILP model which schedules the charging events and quantities as cheap as possible using the DAM pricing for electricity. To see how robust this new schedule is, we created a validation model which uses stochastic trip times and electricity usages to simulate the real operations of the bus schedule. Using the results presented in Chapter 10 we can now answer the research question. Remember that we formulated our research question, in Section 3.1, as follows:

Does the scheduling of charging moments and quantities in an existing bus schedule using day-ahead market information lead to a difference in electricity costs compared to the initially scheduled charging moments and quantities?

We can see that by using DAM information we are able to reduce the charging costs significantly. When comparing the MILP model to the standard model, we note a cost reduction between 28.8% and 31.4%. This is a theoretical cost reduction, as this only happens when every bus is exactly on time and uses exactly the stated electricity consumption rate. When we compare the validation model with the standard model we see a cost reduction between 22.0% and 23.9%. This cost reduction reflects a more feasible difference as we simulate the real operations of the bus schedule, with departure and arrival times deviating from the planned times, as well as a variable electricity consumption rate.

However, both models do show that using DAM information for the scheduling of the charging moments and quantities does lead to a difference in the electricity costs. This leads us to conclude that using DAM information for the scheduling of charging moments and quantities is a viable step for a PTO to reduce the electricity cost.

11.2 Future Work

Using the limitations discussed in Subsection 10.2.2 we can state possible options for further research.

DAM prediction The DAM information for the last six hours in each MILP run was expected to be 100% predictable. Unfortunately in the real world this prediction is not so accurate. Future research could focus on the prediction of the DAM pricing to further make the model more feasible.

Rearranging the bus schedule This research focused on rearranging the charging schedule of the buses. Another interesting research option is rearranging the scheduling of the buses in combination with charge scheduling. This way one bus can take over the bus schedule of another bus, allowing the other bus to charge at times when this was not possible in this research. This could further reduce the electricity cost and maybe prevent some buses from running out of battery.

Electricity consumption prediction For the stochastic electricity consumption we used variables which change on a daily basis. To make the stochastic electricity consumption rates more variable and thus more representable, future research could use variables which change at a higher rate, instead of once every day.

Other electricity provider costs The last recommendation for future research is to incorporate more costs for the scheduling of charging moments and quantities. As stated in Section 10.2.2 the cost of electricity itself is not the only cost charged by the electricity provider. Future research could incorporate these costs, such as contract costs and connection costs, in scheduling the charging moments and quantities to make sure that these costs are also minimized as much as possible, therefore reducing the overall electricity costs.

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Part V

Appendices

Appendix A

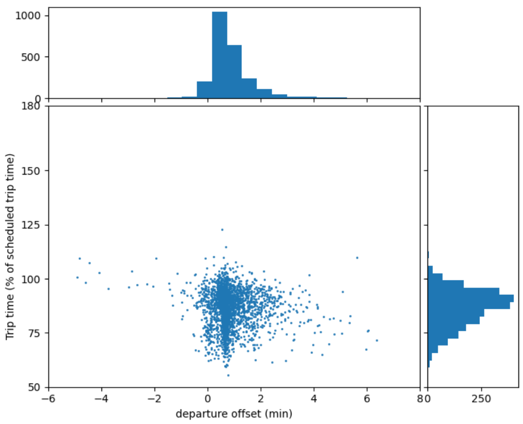
Driving Distributions

On the following pages, we show the distributions of the realised departure times as an offset from the planned departure times and trip durations as a percentage of their original duration time. The data is split up into the three bus lines and the seven time slots which are given below in Table A.1. Generally speaking, buses tend to depart later than the planned departure time, rather than departing before their planned departure time. Trip duration times are also more likely to be shorter than their planned duration, by a small percentage. In the bus schedule there almost always are layover points. These points often have a buffer build in where the arrival and departure time are some minutes apart. When a bus encounters a delay before this layover point, the buffer can hopefully fully cover the encountered delay and thus ensure that the bus is back on schedule. As the trips are generally shorter than 100% of the planned times, this would indicate that the calculated delays of trips, covered by the layover times, due to regular circumstances are rather accurate.

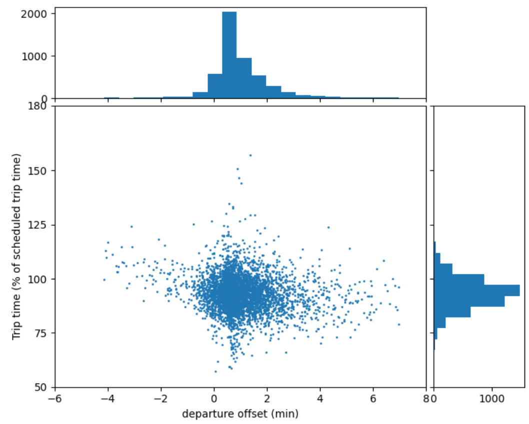
Time Slot	Times
1	4:00-6:59
2	7:00-8:59
3	9:00-11:59
4	12:00-14:59
5	15:00-17:59
6	18:00-9:59
7	20:00-3:59

Table A.1: Time Slots

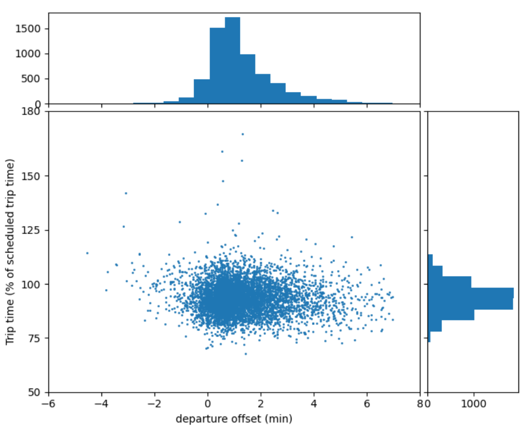
A.1 Line 3



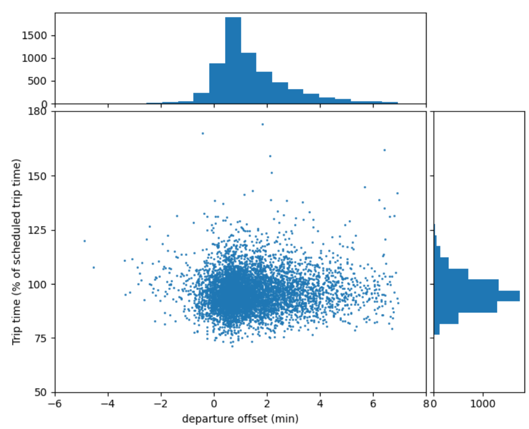
(a) Scatter plot line 3, slot 1



(b) Scatter plot line 3, slot 2

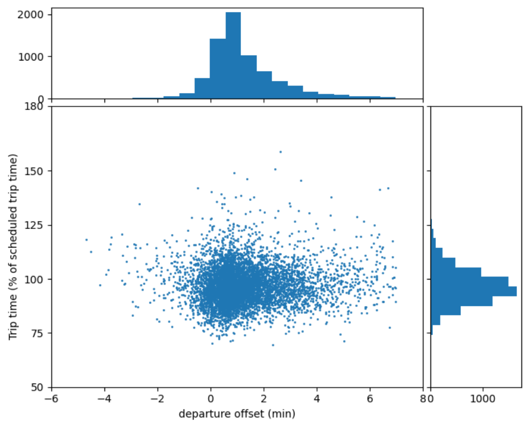


(c) Scatter plot line 3, slot 3

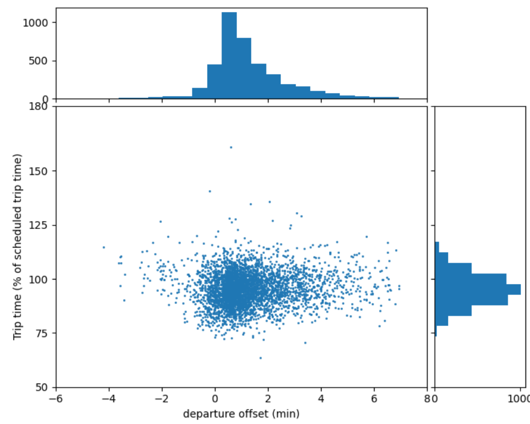


(d) Scatter plot line 3, slot 4

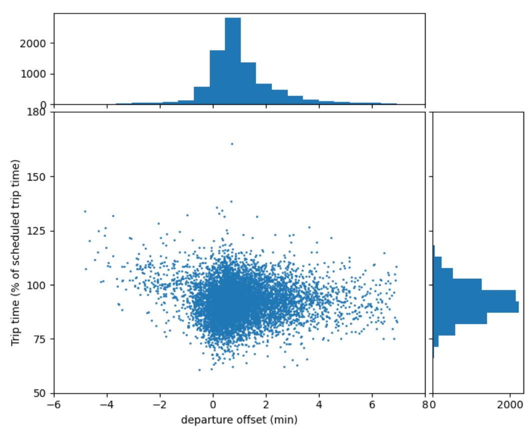
Figure A.1: Scatter plots of line 3, part 1



(a) Scatter plot line 3, slot 5



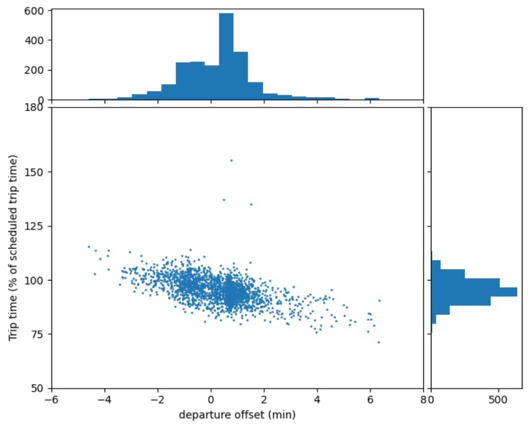
(b) Scatter plot line 3, slot 6



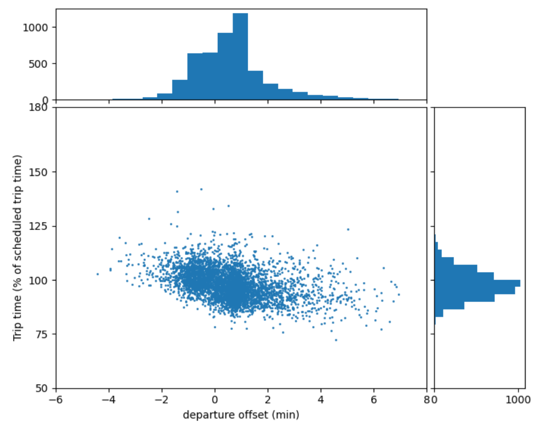
(c) Scatter plot line 3, slot 7

Figure A.2: Scatter plots of line 3, part 2

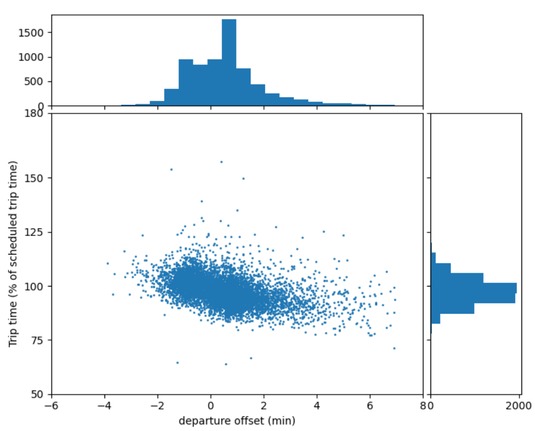
A.2 Line 7



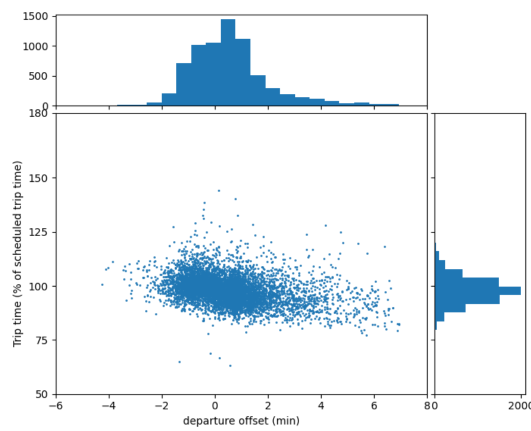
(a) Scatter plot line 7, slot 1



(b) Scatter plot line 7, slot 2

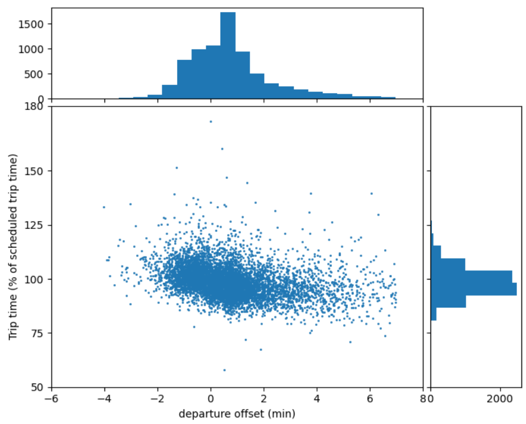


(c) Scatter plot line 7, slot 3

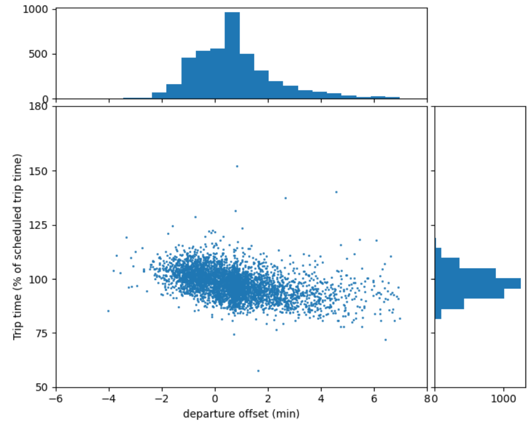


(d) Scatter plot line 7, slot 4

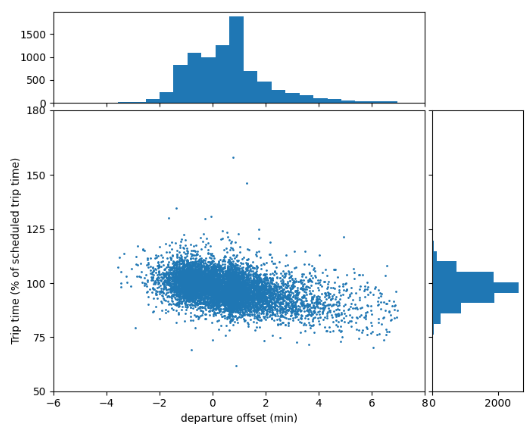
Figure A.3: Scatter plots of line 7, part 1



(a) Scatter plot line 7, slot 5



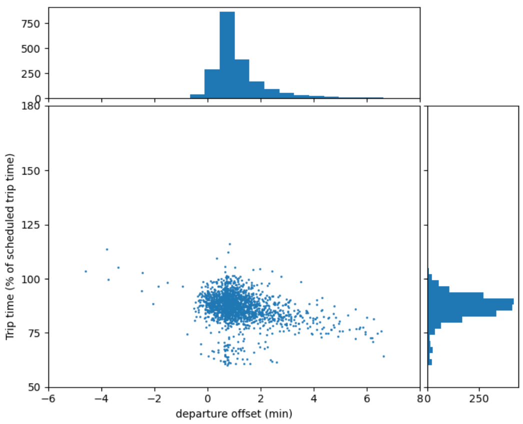
(b) Scatter plot line 7, slot 6



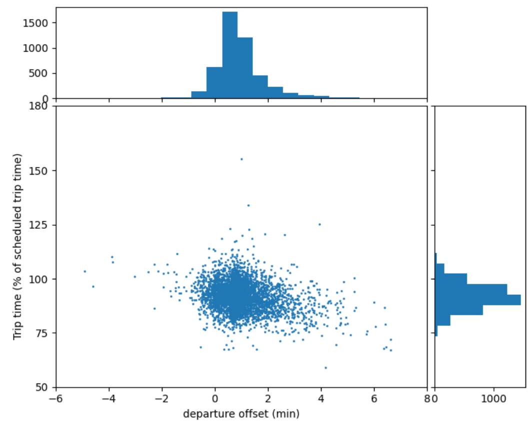
(c) Scatter plot line 7, slot 7

Figure A.4: Scatter plots of line 7, part 2

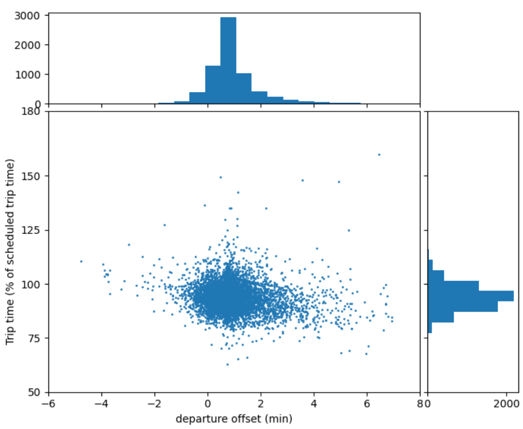
A.3 Line 8



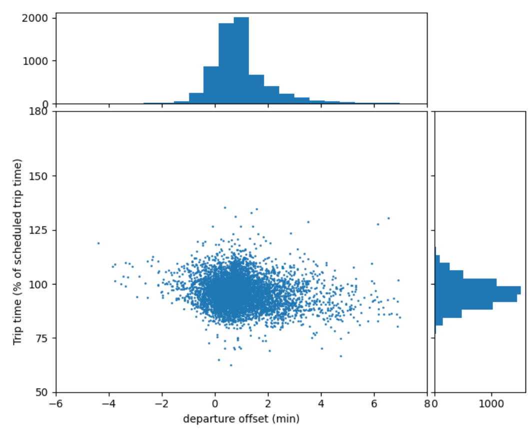
(a) Scatter plot line 8, slot 1



(b) Scatter plot line 8, slot 2

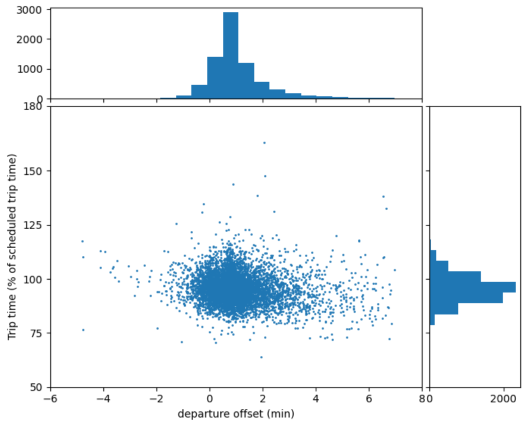


(c) Scatter plot line 8, slot 3

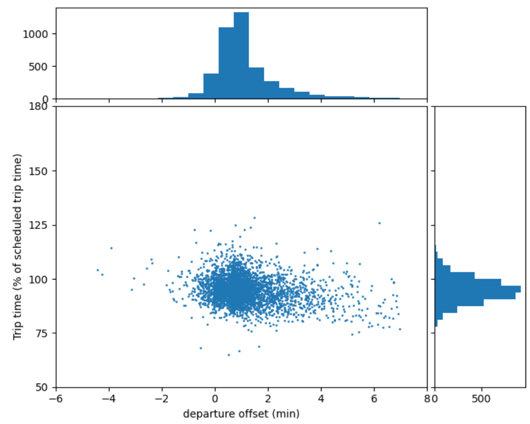


(d) Scatter plot line 8, slot 4

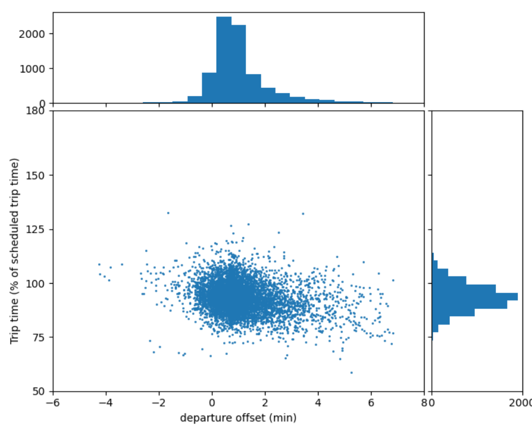
Figure A.5: Scatter plots of line 8, part 1



(a) Scatter plot line 8, slot 5



(b) Scatter plot line 8, slot 6



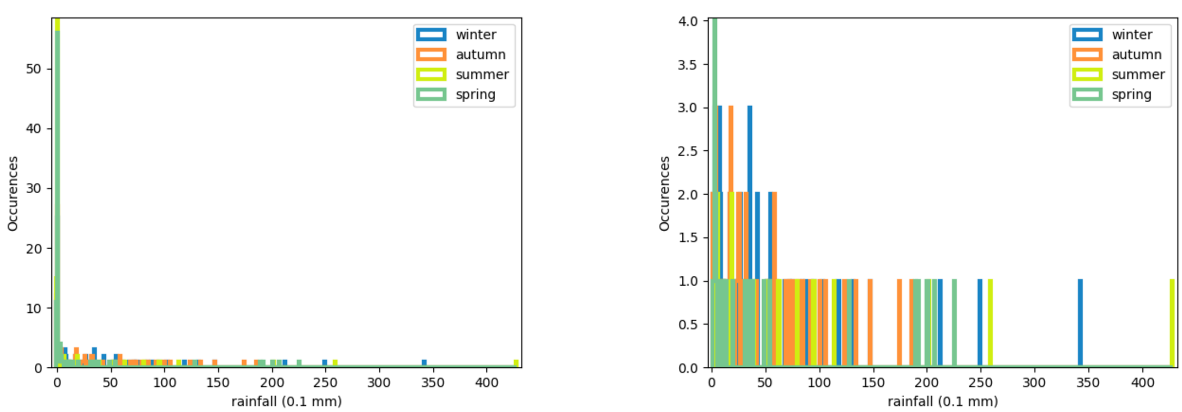
(c) Scatter plot line 8, slot 7

Figure A.6: Scatter plots of line 8, part 2

Appendix B

KNMI

In Figure B.1 we can see both the full rainfall data of the whole year per season and the rainfall of all days with a total rainfall of over 0.1mm. We can see that most days have a rainfall of under 0.1mm. For the days with more rainfall, we notice no particular trend, except that the higher the rainfall within a day, the less it occurred.



(a) all rainfall data

(b) rainfall data ≥0.1mm

Figure B.1: KNMI rainfall

The temperature, as can be seen in Figure B.2, shows the same shape as the one presented in Section 6.2, giving us no extra useful information.

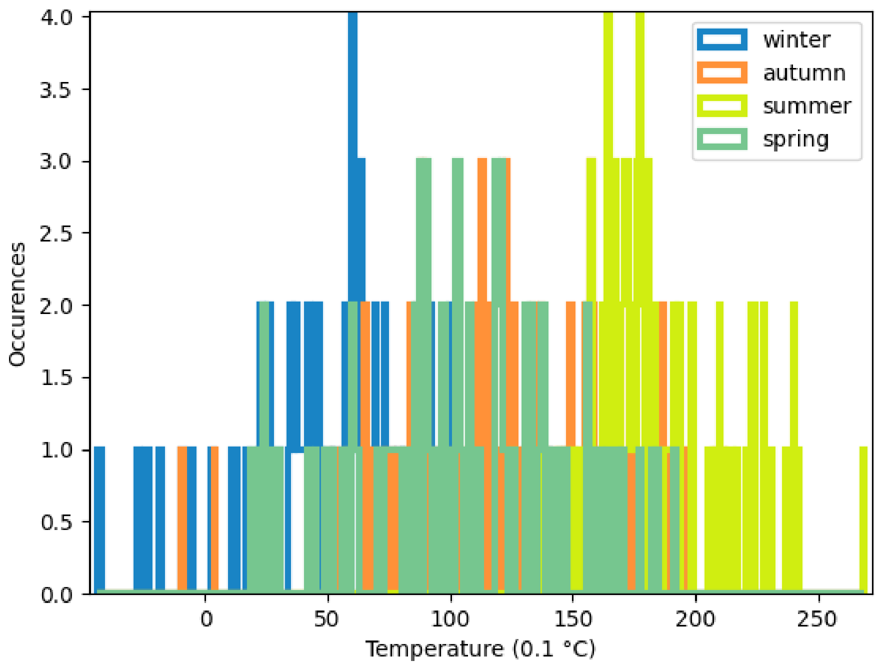


Figure B.2: KNMI temp

The wind speeds presented in Figure B.3 also do not show any irregularities when compared to the less detailed version as seen in Section 6.2.

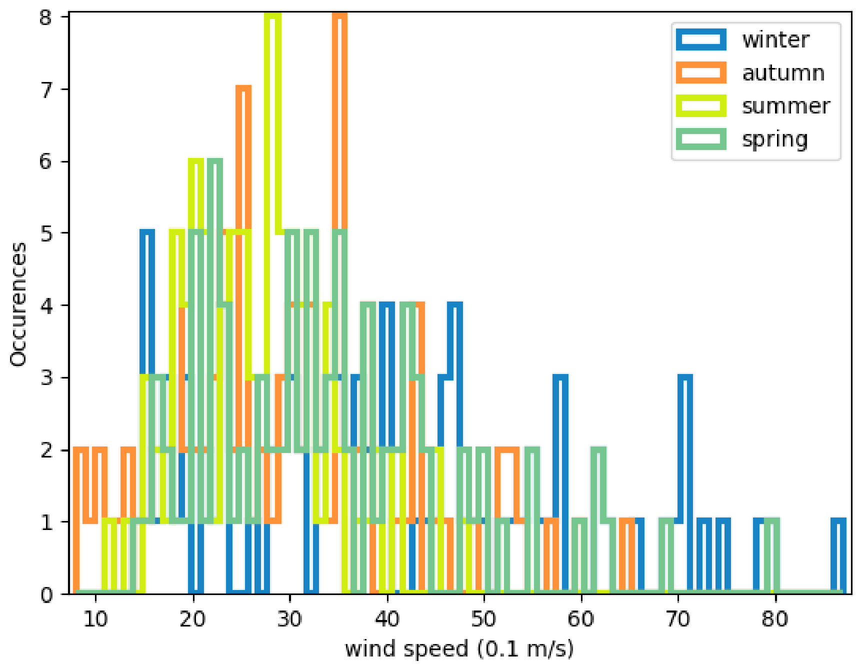


Figure B.3: KNMI wind