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Intelligent Charging Algorithm for Electric Vehicles

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Abstract

Electric vehicles play an important role in creating a fossil free transport sector. Making the vehicles efficient involves many new areas outside the manufacturing process, such as chargers, power grids and electricity markets. This thesis models the charging of electric vehicles using a Markov Decision Process and uses Reinforcement Learning solution models to derive an intelligent charging algorithm. This algorithm can take concepts such as electricity price, battery degradation and electrical losses into account in order to minimise the overall operational costs, and add more value to the use of electric vehicles. Models of how voltage varies in a battery is used and data on causes of battery degradation are derived from modern papers within battery technology. The intelligent charging algorithm is compared to baseline charging algorithms, one of which correspond to how charging is regularly performed today. Vehicle-to-Grid is a promising future technology where electric vehicles can discharge some of their energy back to the grid in order to alleviate the stress of a power grid constrained by increasing demand as well an increasing penetration of intermittent sustainable sources of electricity such as wind and solar. Simulations are performed over scenarios with different electricity prices and the implications of being able to utilise Vehicle-to-Grid is studied. Results from simulations show that the intelligent charging algorithm effectively can reduce costs by approximately 30% on average compared to regular charging when the charging sessions last for 7 hours. Vehicle-to-Grid was seen to only be able to reduce costs in simulations with inexpensive batteries on days when there was a large difference in electricity price. The intelligent charging was able to save as much as 500 SEK for long charging sessions with expensive batteries, and powerful chargers. Results show a promising future for an intelligent charging algorithm to be used in order to improve the efficiency of electric vehicle charging.

Sammanfattning

Elektriska fordon spelar en viktig roll för målet att skapa en tranportindustri som inte förlitar sig på fossila bränslen. Utmaningen att göra elektriska fordon så effektiva som möjligt innefattar många nya områden som ligger utanför det faktiska tillverkandet, som laddinfrastruktur, elnät och marknader för elektricitetshandel. Detta examensarbete modellerar laddning av elektriska fordon med Markov-beslutsprocesser och använder algoritmer från förstärkt inlärning för att ta fram en intelligent laddalgoritm. Denna algoritm kan ta indata från koncept som elpris och batteridegradering samt räkna med elektriska förluster, allt för att minska driftkostnad och göra det mer värdefullt att använda elfordon. Modeller för hur spänning varierar används och data för hur batterier degraderas används från moderna rapporter inom batteriteknologi. Den intelligenta laddalgoritmen jämförs med andra tillvägagångssätt att ladda, bland annat ett som motsvarar hur laddning ofta utförs idag. Vehicle-to-Grid är en lovande framtida teknologi som innebär att elektriska fordon kan ladda ur energi ur sina batterier och sälja tillbaka till elnätet för att reducera belastningar i nätet, dels på grund av ökad efterfrågan men också på grund av att elnätet i framtiden kan bestå av mindre pålitliga men förnyelsebara energikällor som solceller och vindkraft. Simuleringar körs över situationer med olika elpris och effekterna av att kunna använda Vehicle-to-Grid studeras. Resultat visar på att intelligent laddning kan spara ungefär 30% av kostnaderna i snitt. Simuleringarna visar att Vehicle-to-Grid endast kan spara kostnader då batterierna är billiga och då elpriset uppvisar stora variationer. Den intelligenta laddningsalgoritmen kunde spara upp till 500 SEK vid laddsessioner som varade en lång tid, med dyra batterier och med kraftfulla laddare. Resultaten visar på en lovande framtid för intelligenta laddalgorimer att användas för att öka effektiviteten inom laddning av elektriska fordon.

Acknowledgements

I would like to thank my supervisors Andreas Zafeiropoulos and Mathias Björkman, as well as the whole department at Scania. Thank you for your support and for welcoming me with open arms into your world of electrification. It will be exciting to watch what you and Scania create in the future, and I wish you all the best.

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Contents

Chapter 1

Introduction

The growth of the economy as a whole is linked to the growth of the transport sector – a strong economy will have a strong need for transporting goods and people, hence causing the fleet of transportation to grow with it. This relationship is one of many reasons for the need of transport to become increasingly sustainable – as a transportation industry relying heavily on fossil fuels grows together with the economy it means that its contribution to climate change grows as well, an effect that in turn has potential to cause substantial negative economical impacts [1]. A decoupling of this unwanted effect is needed for the economy and transport sector to be able to grow in a sustainable way – for the economy to be able to grow without simultaneously increasing the risk of declining.

Electrification is one of the promising technologies to make transport increasingly fossil free, by charging electric vehicles that are carrying batteries with electricity generated from fossil free sources such as hydro, wind and solar. However, there are many new challenges that are brought to the table along with the use of electric vehicles aside from the actual manufacturing, especially for commercial vehicles. Charging the batteries is of utmost importance for maintaining the batteries in good condition [2, p. 59], and batteries are the single most expensive part on an electric vehicle [3]. This makes the operation of charging carry large economical responsibilities.

Developing a network of chargers that can support a large market penetration of electric vehicle will need considerable planning on changes in the power infrastructure [2, p. 81], especially if the electricity increasingly comes from sustainable but less reliable and intermittent sources such as solar or wind that depends on the weather [4, p. 25]. Another challenge is the nature of the electricity market, where the price of electricity can change throughout the day depending on the demand, which can affect the costs associated with operating electric vehicles.

All of these challenges implies that the focus for transport improvements in an electrified world will no longer mostly be centred around technologies that solely exist on board the vehicle itself, but rather be shifted towards interconnected technologies such as electricity generation, power grid systems and charger networks. The challenge of providing the most efficient solutions and products hence involve technologies and areas spanning far and wide – areas that might not be traditionally associated with the transport sector. Suddenly there is a need for vehicle manufacturers to be involved with power companies, expansions of the electricity grid and to coordinate their solutions with the variable electricity market in order to provide the most valuable transport solution for their customers.

Reinforcement Learning is a branch within Machine Learning that can be said to be the computational equivalent to *learning by interacting*. Problems are modelled and formalised in terms of sequential decision making using Markov Decision Processes, where the actions that are taken influence immediate and subsequent rewards as well as the surrounding environment of the decision maker. Solution methods within Reinforcement Learning can solve the challenge of deriving the optimal *policy*, the best decisions to choose with regards to the cumulative reward. Reinforcement Learning has seen recent success in solving a broad variety of problems, from being used in algorithms to defeat professionals in board games such as Chess and Go, to aircraft flight control [5, ch. 16].

The main focus of this thesis will be within the area of charging electric vehicles, to study optimal strategies to follow when charging an electric vehicle, and to investigate the potential monetary gains to the use of intelligent charging algorithms from a Computer Science perspective.

1.1 Purpose

The high power-train efficiency of combustion engine vehicles manufactured today by companies such as Scania is the product of many years of experience, innovations and improvements. When shifting to electric powertrains there are a multitude of new areas with potential to be improved in order to reach a level similar to the modern highly advanced technologies seen in vehicles with combustion engines. Some of these areas that are relevant to the investigations of this thesis are listed below:

- Electricity prices can go up and down, in some cases as often as every hour [6]. The electricity market will be studied in more detail in Section 2.1, though for now it is enough to know that prices can vary – and the differences in price can be of substantial size. How does this affect the operations of electric vehicles? In order to be the most efficient here one should try to charge the batteries when prices are low [7].

- The quality and performance of batteries in electric vehicles degrade over time and use [3, 8, 9]. Battery assets are expensive components [3], hence the health of the battery will have potentially large impacts associated to the total cost of operating the vehicle. The issue of charging is of utmost importance to maintain batteries in good condition [2, p. 59]. Charging and using the battery assets in a way that damages them as little as possible is essential for the overall efficiency of a vehicle [10, ch. 9]. For commercial operations this becomes increasingly important, since even smaller percentages of savings can result in large savings over a whole fleet, and margins for profit can be stretched thin [11, p. 70].

- Electrical losses means that faster charging using more power will result in larger losses due to for example heat dissipation [12]. This will affect the costs associated to charging an electric vehicle. In the case of filling up a fuel tank on a combustion vehicle this would be analogous to spilling an increasingly larger share of the fuel on to the ground the faster you pour gasoline into the tank.

- Charging stations does not work the same and does not have the same capabilities – the power available could differ from one charging station to another [13]. Again, this type of problem is not usually encountered with fuel for combustion engines. The most efficient use of electric vehicles would be able to account for this in order to get the most efficient type of operation.

- Large-scale integration of electric vehicles can significantly stress the electricity supply side, with problems related to grid frequencies, fluctuations and peak usage [14]. With fuel and combustion engines filling up the tank is mostly not of any concern. Regions and areas where combustion vehicles operate have for many years had a well working system of providing fuel to end customers. For the electric equivalent to filling up fuel, charging batteries, the situation looks different. Limitations in the existing hardware as well as within the electricity production might make charging vehicles, especially heavy commercial ones, a challenge to the whole system [15, 2, pp. 15, 81]. However, electric vehicles and their batteries can at the same time provide valuable benefits to the grid using technologies such as Vehicle-to-Grid [15, p. 15].

The purpose of this thesis is to investigate the potential improvements as well as their reach within the areas listed above by the use of Computer Science applied to electric vehicle charging. More specifically this means how electricity price, physical effects present in battery charging and operational constraints can be taken into account in order to reduce the cost of charging, and hence reduce the costs for electric vehicle operation as a whole.

1.2 Research Question

The research question of this thesis, following the purpose and the introduction of electric vehicle operations, reads as follows:

- With the use of Machine Learning methods, how much value can be added to the use of electric vehicles by creating a realistic solution that can plan the battery charging in a way that minimises cost?

A realistic solution here is seen as one that can take many of the factors that exists in real battery charging into account. It is deemed that this thesis will have made progress in research regarding improving electric vehicle operation from a Computer Science point of view if this question can be answered in this study.

1.3 Relevance

The work is scientifically relevant since both the areas of electric vehicles and Machine Learning are under much development within the areas of transportation and Computer Science, respectively. The use of Computer Science and Machine Learning methods to derive solutions for charging of electric vehicles is of relevance, since it is interdisciplinary and not well studied. Since this thesis will be developed in close collaboration with Scania it is likely that the results from the thesis could provide value for Scania and other companies within the industry to solve real challenges they have, or provide value to areas they work within.

Sustainable transport solutions and electrification is of relevance to society as a whole, on a local level contributing to cleaner air in cities and communities and on a global level reducing climate change. Research in the area of making electric vehicle transport solutions increasingly efficient is hence relevant too, making it more valuable to shift to electric powertrains and enabling the shift earlier by shortening the gap to the cost efficiency of combustion engines.

1.4 Delimitation

The thesis will not focus on implementing something that is directly usable and can be integrated into the existing solutions and infrastructure of Scania. The scope of the thesis is of a more theoretical nature and should rather serve as a proof of concept. Many of the areas within electrification and battery technology are new, and not all parameters involved are well known. Lengthy and substantial research on high academic levels are performed within the area of battery degradation. This in combination with the fact that the main scope of this thesis lies within Computer Science makes for delimitation within the areas of battery degradation, battery technology, vehicle technology and electrical engineering. Although such concepts will be used in the thesis, they will be studied in terms of their role in a Computer Science model rather than being studied or contributed to on their own.

In order to develop realistic solutions there are several parameters involved within the models of this thesis, such as parameters within the battery specification and the charging session environment. Only a limited number of combinations of values set to these parameters will be investigated, the full picture of how different values set to all of these parameter affect one another will not be studied in great detail.

1.5 Thesis Outline

The following chapter is Chapter 2, Background, where the background to electric vehicle operation and related technologies as well as the theory behind Reinforcement Learning are brought up. Finally the chapter lists existing research within the area of intelligent charging.

The next chapter is Methods, Chapter 3, which describes the methodologies behind setting up the simulations and models, which simulations will be ran and the software and technologies used.

Chapter 4, Results, is the following chapter, which shows the results from simulations, how the modelled intelligent charging algorithm perform compared to baseline charging algorithms in different circumstances.

Following Results is Chapter 5, Discussion, which discusses possibles sources of errors, explanations to the findings, the thesis from a sustainability perspective and future work.

Conclusions, Chapter 6, is where the thesis is concluded.

Chapter 2

Background

This chapter describes electric vehicle operations and related technologies, as well as the historical background to electrification. Scania as a company is briefly described, together with some of its current products and electric vehicles. Finally the theory behind Reinforcement Learning is brought up, together with existing research within intelligent electric vehicle charging.

2.1 Electricity Market

The International Energy Agency (IEA) states that out of all of its members counties, Sweden has the lowest share of fossil fuels in its primary energy supply [16]. It is said that the electricity generation in Sweden is practically decarbonised thanks to a large access to hydro, nuclear and wind power, and that Sweden has the second lowest CO_2 emissions per GDP (Gross Domestic Product) and per capita among the member countries. It is possible for electricity to be produced with little emissions of CO_2 today, even if that is not the case in many countries [17].

Nord Pool is is the leading power market in Europe, during 2019 a total of 494TWh was traded through Nord Pool [18, 19]. More than 95% of the energy consumed in the Nordics and Baltics is traded through Nord Pool [20]. The electricity price for end customers on Nord Pool vary by the hour, and are set and published the day before [6]. While some contracts are based on the hourly prices, not all electricity contracts are [6, 21]. Many utility companies has been adopting real-time electricity prices to encourage shifting energy usage to off-peak hours [22]. If the hourly prices are what the customer pays for the electricity, cost can be lowered if consumption is decreased during hours of high prices [23].

In Sweden there are four different price regions, region 1 in northern Sweden down to region 4 in southern Sweden [6]. See Figure 2.1 for an example of hourly prices in region 3.

There can be big differences in the electricity price for the different hours of the day, which can be seen in the example of Figure 2.1. One night in January 2020 the electricity price was 99% lower than the usual price levels [24].

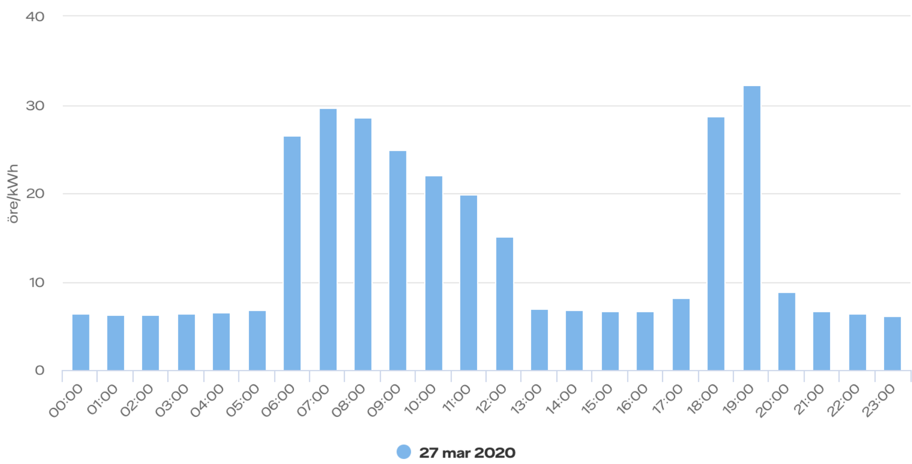

Figure 2.1: *Electricity prices in SEK öre/kWh each hour on March 27, 2020 Vattenfall [6]. Price region 3, southern-middle Sweden.*

Industry and buildings accounted for over 90% of the global electricity demand in 2019, while transport made up less than 2% [25]. IEA describe that in a *Stated Policies Scenario*, when taking the existing policy frameworks and today's ambitions into account [26], the global electricity demand is predicted to grow by 2.1% per year to 2040. The rising electricity demand was one of the key reasons why global CO_2 emissions reached a record high in 2018, electricity demand growth is predicted to be particularly strong in developing economies [25].

2.2 Transport Sector

2.2.1 Globally

The transportation system of today is highly dependent upon nonrenewable fossil fuels [27]. Economic growth is closely associated with growth in road freight activity according to IEA [28]. Furthermore, it is said that around 65% of road freight activity is accomplished by heavy-freight trucks. It is described that although heavy-freight trucks are the most efficient for hauling cargo on roads, their large annual mileage result in a consumption of half the oil in the road freight sector.

The oil demand from road freight vehicles account for around one-fifth of the global oil demand, equivalent to the oil production of the United States and Canada combined [28] – passenger cars account for around one-quarter of the total oil demand. While the oil use from cars has begun to decline in many industrialised countries the oil use from road freight vehicles has continued to rise [28]. Road freight transport relies heavily on diesel, the demand account for about half the global diesel demand [28].

2.2.2 Europe

Previously passenger cars were the main contributor of tailpipe emissions amongst the transport sector in Europe says Svens, Behm, and Lindbergh [29]. However, it is stated that in recent years trucks have become the main contributor. It is said that the transport sector is responsible for 28% of the CO_2 emissions in Europe, with heavy-duty trucks responsible for almost half of those.

Trucks over 16 tonnes had the largest market share of the EU-28 group of countries in 2018, around 70% within the truck and bus segment [30].

2.3 Electric Vehicles

2.3.1 History

At the turn of the 20th century the horse was still the primary source of transportation in America, according to U.S. Department of Energy [31]. It is stated that as Americans grew more prosperous they turned to motor vehicles, available in steam, gasoline or electric versions. Electric cars quickly became popular with urban residents, especially women, see Figure 2.2. The first successful electric car in the U.S. came in 1890. As more people gained access to electricity in the 1910s it became easier to charge electric cars, adding to their popularity. The founder of Porsche, Ferdinand Porsche, developed an electric car in 1898. When Henry Ford's mass-produced Model T came it was more affordable than its electric counterparts. By the 1920s the U.S. road system had grown which increased the demand for longer trips. Then came the discovery of Texas crude oil, and gasoline became cheap and readily available for rural

Americans. By comparison few outside the cities had access to electricity. Electric vehicles had all but disappeared by 1935.

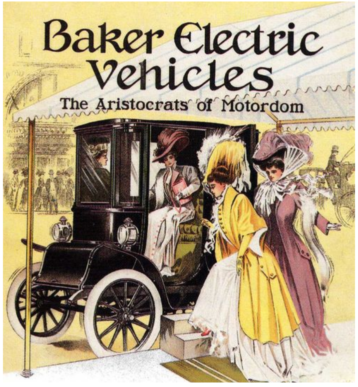

Figure 2.2: *Baker Electric Vehicles advertisement, 1910. "It is noiseless and clean; having a battery capacity of 70 to 100 miles, it is unequalled for city and suburban use" [31].*

2.3.2 Today

A driving force for electric vehicles is a future shortage of oil, which implies an economic risk to be dependent on oil for transport [17]. Electric vehicles are among the most effective technologies to alleviate an unsustainable dependency to oil [27].

> *"Although they are only at a relatively embryonic stage in terms of market penetration, EVs represent the most environmentally friendly vehicle in terms of fuel because they have absolutely no tailpipe emissions."* - Leitman [10]

The global stock of electric passenger cars passed 5 million in 2018, says IEA [32]. This was an increase of 2 million cars, from the previous year. Furthermore around 45% of the electric cars on the road were in China, 24% in Europe and 22% in the United States. IEA continue to state that by the end of 2018 there were around 460 000 electric buses, 250 000 electric light-commercial vehicles and 1000-2000 medium electric trucks in the world. Those medium electric trucks are mostly concentrated in China. The electric car market share in Norway is said to be 46%, which is the highest in the world, followed by Iceland and Sweden with 17% and 8% respectively. IEA state that in 2030 the stock of electric vehicles is expected to have grown to between 130 and 250 million, and the global sales are expected to be between 23 and 43 million by then.

From a well-to-wheel perspective, the greenhouse gas emissions from electric vehicles will continue to be lower than for vehicles with internal combustion engines [32]. A modern truck with a combustion engine can achieve efficiencies from engine to wheel no higher than 30% while an electric truck can reach powertrain-to-wheel efficiencies of 85% [28]. Operating an electric vehicle that is charged with electricity generated only from coal plants will still be cleaner than a vehicle with a combustion engine [10].

There are cost implications for the large battery requirements in trucks [28]. A solution to reducing the battery needs can be through the supply of electricity to vehicles while in motion – electric road systems. However, electric road systems require high investment costs [28].

2.4 Batteries

A battery is the most expensive component of an electric vehicle [3]. Lithium-Ion batteries provide one of the best energy-to-weight/volume ratios and exhibit appealing features [33]. This has pushed electric vehicle industries to adopt Lithium-Ion batteries [33, 3]. The costs of Lithium-Ion battery packs has declined, and costs among market leaders are much lower than previously reported [34]. This could have significant implications on the modelling of future energy and transport systems and would permit an optimistic outlook for electric vehicles contributing to low-carbon transport [34]. Energy - Vehicle Technologies Office [35] states a battery cost of US$125 per kWh as a 2025 target. A battery cost of US$150 per kWh is said to commonly be considered as the point of commercialisation of battery electric vehicles [34]. An 8% annual cost decline for Lithium-Ion market-leading battery packs in electric vehicles is expected, and a 14% decline for the industry as a whole [34]. From 2010 to 2019 the price of an average Lithium-Ion battery back has decreased by over 80% [3].

2.4.1 Battery Degradation

Battery State of Health is a measure of how much energy can be delivered. A battery starts with 100% State of Health and deteriorate to lower values over time [3, 8]. The degradation of a battery unit over time is not linear [3], see Figure 2.3. The reduction of the battery power delivery capabilities is called *power fade* [8]. State of Charge is how much the battery is charged, expressed as a percentage from 0% to 100%. The measure State of Health is important to use when defining a battery asset as End of Life, when it has deteriorated to a level where it is not usable anymore. There are currently no standard definition of End of Life, but a common view is that 20-30% reduction of capacity [8, 36] or a 100% increase in power fade is what constitute End of Life [8]. Hence an End of Life battery still has 70-80% of its initial capacity left. This has lead to investigations on battery second life applications, such as stationary power storage systems [8]. One study show that batteries for electric vehicles effectively can meet the needs even beyond the commonly accepted threshold of 80% remaining capacity [9].

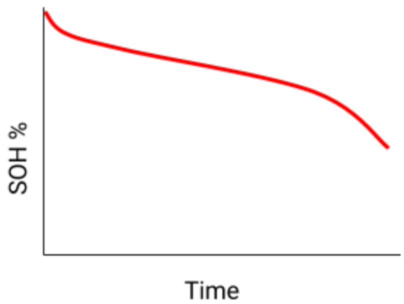

Figure 2.3: *Example of the variations of State of Health (SOH) of a battery over time [3]*

There are two categories of battery degradation, or battery ageing [8]. These two are calendar ageing and cyclic ageing. Calendar ageing is described as the degradation experienced when the battery is at rest. It depends on the temperature and State of Charge of the battery as it stays unused. Cyclic ageing is said to be the degradation resulting from battery usage and is dependent on the temperature, State of Charge, charge current (C-rate). C-rate is a representation of charge current normalised by battery capacity, such that 1C would discharge a battery in one hour and 2C in 30 minutes [8].

> *"Battery degradation is a natural process that permanently reduces the amount of energy a battery can store, or the amount of power it can deliver."* - Argue [3]

High temperatures trigger more battery degradation [3, 8]. High temperatures specifically trigger more calendar ageing. Low temperatures and high C-rates induce more cyclic ageing [8].

Ways to minimise calendar ageing while the battery is at rest is to maintain a low State of Charge and a lower temperature. To minimise cyclic ageing when the battery is in use a moderate temperature, moderate C-rate and a low depth of discharge centered around an optimal State of Charge point should be maintained. More research is necessary on this, but the optimal cycling point is assumed to be around 50% State of Charge [8].

Temperature is the most prominent environmental cause of battery degradation. Having the right temperatures will mitigate degradation from temperature, but will also have positive effects on the degradation from other factors, such as C-rate [8].

Calendar ageing is the most dominant reduction factor of battery lifetime for passenger electric vehicles, since most passenger vehicles are immobile more than 90% of the time. Hence the performance of a battery is largely determined by how it is managed while at rest [8].

With this in mind the best battery management strategy should be based on three principles [8]:

1. Minimise temperature rise within the battery.
2. Minimise the time spent at high State of Charge.
3. Minimise average charging power (C-rate).

The relatively simple strategy of starting to charge just in time to be able to reach the target before having to leave will outperform the typical strategy of starting to charge as soon as the vehicle is plugged in [8].

Wikner [37] investigates the impact of temperature, current and State of Charge on batteries for vehicle application and results show that battery lifetime in a vehicle application could be prolonged by planning of the charging:

> *"... battery lifetime in a vehicle application could be prolonged, without interfering with the driving itself, by better planning of the charging"* - Wikner [37]

2.4.2 Vehicle-to-Grid

Renewable energies are a key pillar in decarbonisation of the power sector says Uddin et al. [38]. However, it is said that they come with a backside of variability and uncertainty. This is described to increase the need for energy storage, which in turn is expensive. It is stated that a promising solution is using the batteries contained within electric vehicles. Vehicle-to-Grid hence stipulates using an electric vehicle battery to provide electric services for the power grid [38, 39, 40].

The term Demand Response describes coordination of the energy consumption of electricity customers to ensure a demand-supply balance and reliable grid performance [41]. Vehicle-to-Grid can be seen as a Demand Response technique.

With electric vehicles already connected to the power grid when charging, using Vehicle-to-Grid the vehicle can not only buy electricity but also sell, says Sadeghianpourhamami, Deleu, and Develder [41]. Vehicle-to-Grid is described as a relatively new area of research, and have only been implemented in a few pilot projects. Vehicle-to-Grid can be beneficial in a number of ways to the power grid – Khatiri-Doost and Amirahmadi [39] describe how charging and discharging of electric vehicles can be used in smart grids. The paper specifically covers peak shaving and power losses minimisation. The area where Vehicle-to-Grid can be of most value is frequency regulation according to Noel [40]. Grid quality and stability is described as requiring a constant fine-tuning of the frequency, due to differences between power delivered and power consumed in the grid.

Using an electric vehicle battery for Vehicle-to-Grid will affect the battery degradation, since it means more use of the battery [42]. Instead of charging and discharging to power the vehicle, additionally with Vehicle-to-Grid discharging also occur when selling electricity. Some claim that Vehicle-to-Grid negatively affects the battery [42], while others claim the opposite. The authors of [38] develop a comprehensive battery degradation model based on long-term degradation experiments on commercial batteries. The authors show that not only can Vehicle-to-Grid services help the power network, but more importantly that Vehicle-to-Grid can *extend* the life of an electric vehicle battery – in a studied scenario using a smart car park for load levelling of a commercial building the Vehicle-to-Grid setup was able to reduce power and capacity fade with around 10%.

2.5 Electrical Losses

Electrical losses is the dissipation of energy in an electrical system, for example energy lost from unwanted heating of resistive components [12]. The electrical losses grow as current and resistance in the system grows. In an electric vehicle the losses and the heating associated with it can cause even more *"losses"*, since the vehicle may have to counteract this by using additional energy on cooling components down.

2.6 Scania

Vagnfabriksaktiebolaget i Södertelge (Vabis) was founded in 1891, with operations to manufacture railway rolling stock [43]. The first motor vehicle was built in 1897 and the first truck in 1902. In 1900 Maskinfabriksaktiebolaget Scania was founded in Malmö, where it started building bicycles. Vabis and Scania merged to form Scania-Vabis in 1912. Today Scania has 52 000 employees working in 100 countries [44]. Out of those 4 200 are employed in research & development. Scania is a part of Traton Group, together with commercial vehicle manufacturer MAN among others [45]. Traton is a wholly owned subsidiary of Volkswagen [46].

Climate change, population growth and urbanisation are all challenges within the transport sector. Scania want to drive the shift towards a sustainable transport system with smart & safe transport, energy efficiency and alternative fuels & electrification [47]. Smart transport means applying techniques such as production flow management and vehicle connectivity to achieve the most efficient transport solutions. In terms of energy efficiency, Scania provides energy-efficient products and solutions, such as high powertrain performance and services providing information and tips to the driver.

Scania has since the 1980s explored the possibilities of electrifying buses and trucks [48]. In 2017 Scania introduced a field test of battery electric buses in Östersund in northern Sweden [49].

In February 2020 Scania deployed battery electric vehicle distribution trucks for heavy transport to a wholesaler in Oslo, Norway [50]. The battery capacity of the trucks were 165 kWh with a range of 120 km. In May 2020 it was announced that Scania would continue to deliver 75 more vehicles within the collaboration [51].

2.7 Reinforcement Learning

This section describes the theory behind Reinforcement Learning, as well as how it has been used in the area of electric vehicle charging. The theory presented in this section comes from Sutton and Barto [5] and Puterman [52].

How learning is carried out in nature, for example how we humans learn, is intuitively quite similar to how learning is considered in Reinforcement Learning – learning by interacting with an environment. When interacting with an environment, conclusions about outcomes can be drawn, about the long term or short term effect stemming from different situations. Reinforcement Learning is the computational approach to learning by interacting.

2.7.1 Markov Decision Processes

Reinforcement Learning is learning what to do – how to map situations to actions in order to maximise a cumulative numerical reward. The actions that it is possible to take are known, but their outcome and how they affect the environment is not known. It must be discovered which actions yield the most reward by trying them, and how those actions at the same time affect future chances of high rewards. The learner and decision maker is often called an *agent*. Markov Decision Processes are a formalisation of sequential decision making, where actions influence immediate rewards as well as subsequent situations and rewards. Markov Decision Processes are mathematically idealised forms of Reinforcement Learning problems, see Figure 2.4. The environment changes through time, with time being divided into a number of *decision epochs*. The agent decides what action to take for each decision epoch. A Markov Decision Process according to Puterman [52] contain the following five sets:

- Decision epochs, T. The decision epochs can be finite or infinite, discrete or continuous. In the discrete case, which will be considered in this thesis, T can be formulated as $T = \{1, 2, 3, ..., N\}$, where $N \leq \infty$. Single elements of T are denoted as t.

- States-space: $\mathcal{S}$. The states represent the environment the agent can find itself in and act upon using actions. Different actions will constitute different transitions to states from the current state of the agent.

- Action-space: $\mathcal{A}$. The action-space contain the possible actions that the agent can take. Actions are taken by the agent in each decision epoch in order to go from one state to another and receive a subsequent reward.

- Rewards: $\mathcal{R}$. The rewards associate a numerical value to an action taken when being in a certain state. A reward is a function of the time (decision epoch), the state the agent is currently in and the action that is taken – $r_t(s, a)$. It is through the reward signal it can be communicated to the agent what it should achieve. This is not the same as *how* it should be achieved.

- State-transition probabilities: p. The state-transition probabilities denote the probability to from one state take an action and transition to a certain new state.

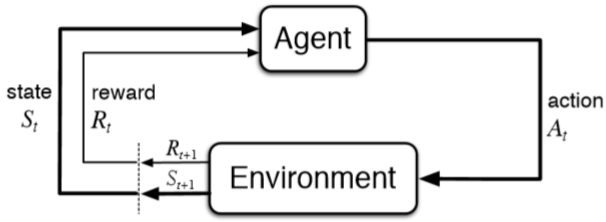

Figure 2.4: *"The agent–environment interaction in a Markov decision process" [5].*

2.7.2 Policies & Learning

A policy, often denoted as π, provides an agent with a way of choosing actions in a given state throughtout the length of an episode. Often much of the problem within Reinforcement Learning consist of deriving the *optimal* policy, the best actions to take. Policies can be randomised as well as deterministic, meaning a policy can return a probability function over the action space or simply return an action. In addition to this, policies can be history dependent or Markovian, the policy can be a function of all previous states and actions, or a function of only the current state. Policies as markovian deterministic is what will be used in this thesis, in other words $\pi_t : S \to A_{s_t}$, that $\pi(s_t)$ gives an action to select.

The objective in Reinforcement Learning problems is to find a policy π that maximises the expected reward:

$$\mathbb{E}\left[\sum_{t=1}^{T} r_t(s_t^\pi, a_t^\pi)\right] \tag{2.1}$$

s_t^π and a_t^π indicate state and action at time t drawn from a policy π. In the case of an infinite time horizon the objective need to be slightly modified in order to avoid infinite cumulative rewards, a *discount factor* is introduced, $\lambda \in (0, 1)$:

$$\mathbb{E}\left[\sum_{t=1}^{T} \lambda^{t-1} r_t(s_t^\pi, a_t^\pi)\right] \tag{2.2}$$

This discount factor λ can control how to value future rewards, a low discount factor will effectively value immediate rewards more than future rewards. It is common to discuss *value functions* in Reinforcement Learning. Value functions represent a way to formalise problems and their solutions, and give a way of assigning a value to certain circumstances within the Markov Decision Process. The value functions are a direct derivation from the objectives, hence solution methods within Reinforcement Learning work on finding or estimating these value functions. The value function $V_T^\pi(s)$ for a finite-horizon Markov Decision Process is formulated as follows:

$$V_T^\pi(s) = \mathbb{E}\left[\sum_{t=1}^{T} r_t(s_t^\pi, a_t^\pi) \,\middle|\, s_1^\pi = s\right] \tag{2.3}$$

$V_T^\pi(s)$ is the average reward achieved under policy π when *starting* in state s. This gives a measure on how valuable it is to start in s, under the policy π. $V_T^*(s)$ can be introduced as the maximal possible expected reward when the initial state is s:

$$V_T^*(s) = \sup_{\pi \in \Pi} V_T^\pi(s) \tag{2.4}$$

The value function $u_t^\pi(s)$ is similar to $V_T^\pi(s)$, but denotes the average reward of being in s at time t rather than starting in s:

$$u_t^\pi(s) = \mathbb{E}\left[\sum_{i=t}^{T} r_t(s_i^\pi, a_i^\pi) \,\middle|\, s_t^\pi = s\right] \tag{2.5}$$

It follows that $V_T^\pi(s) = u_1^\pi(s)$ for any s. Similar to $V_T^*(s)$ of (2.4) $u_t^*(s)$ can be defined as the maximum possible average expected reward going forward from being in s at time t, over all policies:

$$u_t^*(s) = \sup_{\pi \in \Pi} u_t^\pi(s) \tag{2.6}$$

The *Bellman equation* provides a recursive way to compute the value function, and the optimal policy, of finite Markov Decision Processes. It is referred to as *Dynamic Programming* or *Backwards Induction* [52, 5]. $u_t^*(s_t)$ can be estimated by $u_t^{Bellman}(s_t)$, or abbreviated as $u_t^B(s_t)$:

1. For all s_T, $u_t^B(s_t) = \max_a r_T(s_T, a)$. Since this is the last decision epoch the cumulative reward here is the immediate reward.

2. For all $t \in \{T-1, T-2, \dots, 1\}$, and for all s_t:

$$u_t^B(s_t) = \max_{a \in A} \underbrace{\big(r_t(s_t, a) + \sum_{j \in S} p_t(j|s_t, a) u_t^B(j) \big)}_{Q_t(s_t, a)} \tag{2.7}$$

3. The optimal policy is found by assigning $\pi_t(s_t)$ such that $Q_t(s_t, \pi_t(s_t)) = \max_{a \in A} Q_t(s_t, a)$, or in other words: $\pi_t(s_t) = \operatorname{argmax}_{a \in A} Q_t(s_t, a)$

The theory behind the Bellman equation states, after computing u^B using dynamic programming, that $u^B = u^*$.

Solving the Bellman equation using dynamic programming takes $\Theta(S^2AT)$ operations. This represents a considerable reduction in computation compared to exhaustive search, since there are $(A^S)^{T-1}$ deterministic Markovian policies possible, which all would take $(T-1)K^2$ operations to evaluate.

$Q_t(s_t, a_t)$ is another value function, the *state-action* value function. In addition to V_T^π and u_t^π it incorporate actions. Whereas u_t^π denotes the expected future reward from being in a state at time t, Q_t^π denoted the future expected reward from being in a state at time t *and* choosing action a_t. This makes for a way of not only evaluating states, and indirectly actions, but rather associate a value to state-action pairs directly.

This state-action value function is the key element in the algorithm *Q-learning*. Q-learning is a Reinforcement Learning algorithm that is *model free*, meaning it can operate without a model of the environment. By observing decisions and their outcome the quality of an action in a given state can iteratively be approximated, the optimal action-value function is approximated. These observations can come from previous recordings of an agent interacting with an environment. In the example of Reinforcement Learning being used to derive optimal strategies in the board game Go, these previous recordings could come from previous games played by professionals. The policy that yielded the recording or trajectory to be observed is called a *behavioural policy*, denoted as π_b. A requirement on the behavioural policy for *Q-learning* to converge is that all state-action pairs continue to be visited. Q-learning works by continuously making observations on (s_t, a_t, r_t, s_{t+1}) under the behavioural policy π_b, in other words observing action taken from a state, and the associated reward together with the next state. The action-value function is then updated as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\big(r_t(s_t, a_t) + \lambda \max_{a \in A} Q(s_{t+1}, a) - Q(s_t, a_t)\big) \tag{2.8}$$

α is the *learning rate*, and determines to what extent new information overrides old. A learning rate of 0 would effectively never update the action-value function, only make use of prior knowledge. On the other hand, a learning rate of 1 would only exploit new knowledge.

Traditional Q-learning, or *tabular* Q-learning, store the state-action value function in a tabular way, for example in a matrix. This can cause problems as stat spaces and action spaces grown, making a tabular method infeasible. This, together with the previously stated requirement that all state-action pairs continue to be visited for ensuring convergence, makes way for the algorithm *Deep Q-learning*.

Instead of storing the action-value function in a tabular way as in tabular Q-learning it is stored using a *function approximator*, an Artificial Neural Network[1]. Neural networks have good generalisation capabilities, meaning state-action values for state-action pairs that are not within the behavioural policy, that are not learned from, can still be assigned to a value not too far from the truth. This feature becomes essential in large state spaces and action spaces, since it will be impossible to learn from all state-action pairs.

Convergence can become an issue in Deep Q-learning, since (2.8) sequentially and recursively perform updates to the action-value function. This would effectively mean that the output from the neural network is used to update the neural network itself. This is not effective, since a neural network is a supervised learning method, meaning it relies on a ground truth, correctly labelled data, to learn from. There are several ways to alleviate this issue, one of which utilises two neural networks which are handled differently, one acting as the ground truth for the other to use in supervised learning. See Figure 2.5.

2.7.3 Use of Reinforcement Learning for Electric Vehicle Charging Management

Recently Reinforcement Learning has been widely used to make decisions under uncertain scenarios, since it can learn from experience data with less need for modelling the distribution of randomness [14]. Furthermore, the great success of Reinforcement Learning algorithms has inspired researchers to use it for electric vehicle charging management. Model Predictive Control has traditionally been used for problems involving power consumption , says Sadeghianpourhamami, Deleu, and Develder [41]. This is described to have some drawbacks, firstly the modelling task becomes challenging. Furthermore, so-

[1] An Artificial Neural Network is a computing system used for supervised learning, vaguely inspired by biological neurons.

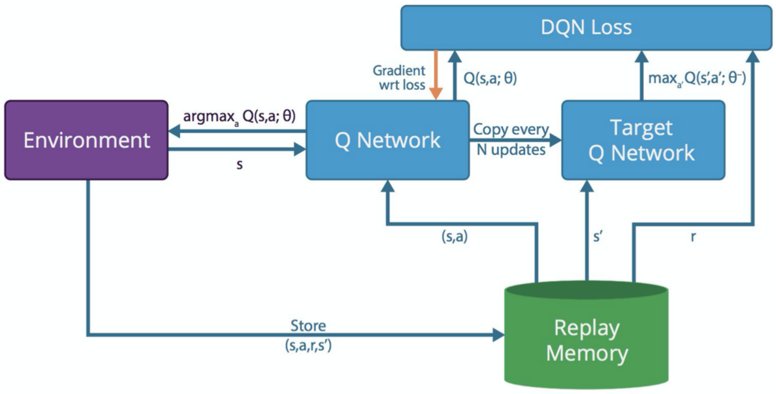

Figure 2.5: *Example of how two neural networks can be used in Deep Q-learning [53].*

lutions become hard to transfer from one scenario to another. It is described that Reinforcement Learning has emerged to facilitate flexibility in algorithms for solving these tasks. In the approaches that make use of Reinforcement Learning technologies the agent interacts with an environment, such as energy market prices and energy providers, and takes actions with the aim of maximising a long term expected reward [41]. This solution method is described as facilitating more practical and generally applicable schemes. One challenge of using approaches that make use of Reinforcement Learning is the curse of dimensionality, that state spaces and action spaces can become very large [41].

Wan et al. [54] develop an electric vehicle charging scheduling method using Reinforcement Learning and Artificial Neural Networks. The vehicle is considered to be either away or at home, where at home charging is possible. The charging actions available, making up the action space, in their model are 7 different charging modes, $-6kW$, $-4kW$, $-2kW$, $0kW$, $2kW$, $4kW$ and $6kW$. Consequently Vehicle-to-Grid is considered, where the negative values correspond to discharging the electric vehicle batteries.

The reward signal $r(t)$ at time t is modelled as follows:

$$r(t) = \begin{cases} -p(t)c - D(c) & t \neq \text{time to leave} \\ -p(t)c - D(c) - \tau(E_{max} - E_t)^2 & t = \text{time to leave} \end{cases} \tag{2.9}$$

Where $p(t)$ is the electricity price at t, and c is the charge action taken at time t. The term $D(c)$ denotes the monetary cost coming from battery degradation, modelled as a cost proportional to the number of cycles of the battery – the degradation is a function of now much the battery has been charged and discharged. $\tau(E_{max} - E_t)^2$ is a punishment for not ending up on the desired maximum energy in the battery when it is time to leave, with τ being a so called range anxiety coefficient, how important it is to achieve exactly a full battery.

The time span considered is 24 hours, with the arrival and departure times of the electric vehicle being modelled as random variables. Q-learning with an Artificial Neural Network as a function approximator of the Q-values, the state-action values, is used. An LSTM[2] neural network is used to model unknown electricity prices. The method is evaluated in two cases, the second one considering battery degradation in terms of cycled energy, how much the battery is used. The battery degradation from cycled energy is a determined by looking at the original battery cost. Different costs are considered which leads to different charging behaviours. In the cases where the battery is more expensive, the amount of cycled energy is minimised, which leads to less Vehicle-to-Grid and sales of electricity.

Electrical losses are not considered, the charge action taken is what the battery is being charged or discharged with. The method is claimed to perform well in simulations, effectively reducing costs compared to uncontrolled charging where the electric vehicle is charged immediately when it arrives home.

The approach proposed in [14] is an extension of [54] and tries to tackle the problem of designing a penalty term in the reward signal for eg. having the electric vehicle not fully charged upon departure. To avoid the process of designing the penalty, and to avoid the possibility of a deteriorating model due to unsuitable penalties, the charging problem of the electric vehicle is formulated as a constrained Markov Decision Process. Furthermore the safe deep Reinforcement Learning paradigm is utilised, a constrained policy optimisation algorithm is developed. Electrical losses are considered, proportional to the charging. Vehicle-to-Grid is considered, the possible actions are charging with $-6kW$, $-4kW$, $-2kW$, $0kW$, $2kW$, $4kW$ and $6kW$. Several baseline approaches are implemented for comparison. The proposed method effectively reduces the amount of violations to the charging constraint, eg. deviations from targeted charging amount, and the amount of charging over and under

[2]An LSTM, Long short-term memory, is a Neural Network structure well suited for time series data.

the boundary values set for the battery. The approach also proved to be cost efficient.

In [55] the authors develop a charging planning algorithm for multiple electric vehicles using Reinforcement Learning. Vehicle-to-Grid is not considered, the vehicles can not discharge and sell energy back to the grid. The cost aimed to be minimised in the approach is the cost of buying electricity on the so-called day-ahead market, electricity is traded the day before it is used, and the cost associated with buying up too much or too little rights of electricity. Their approach is bench marked against a Stochastic Programming optimisation method that knows the fleet setup and timing beforehand, with regards to their performance in terms of electricity costs. This bench mark is used in their evaluation, as well as looking on how their model captures the vehicle flexibility and imbalances in electricity. Results show that the model developed is able to find a day-ahead consumption plan with comparable quality to the benchmark solution without an exact day-ahead model of the electric vehicles charging flexibility.

Machine Learning methods is used in [56] to forecast electricity price and to derive a strategy to charge an electric vehicle that minimises cost. To approximate an action-value function a non-linear kernel averaging regression operator is used. The kernel function and its parameters need to be manually designed. [14] describe this as a drawback. The simulations of [56] show that the charging cost can be reduced with 10-50% compared to a conventional method that is assumed to charge randomly.

Chapter 3

Methods

This chapter describes the methodology behind how the modelling and simulations of this thesis is set up. First the circumstances around the simulations are stated, followed by how the simulations will be performed and evaluated.

3.1 Simulations

The goal of this thesis is to develop simulations for an intelligent charging algorithm, and investigate the implications of using it. The area of the simulations in this thesis is the charging session of an electric vehicle. The charging session of an electric vehicle coming to a charging station and some time later leaving is what is simulated. How vehicles operate before or after the charging session is not considered.

A Markov Decision Process is designed in order to apply Reinforcement Learning solution methods for deriving the optimal policy with regards to cost – a cost that takes battery degradation and electricity costs into account. This policy is what makes up the intelligent charging algorithm, the best strategy to follow during a charging session. Two other baseline charging algorithms, policies, are developed using the same Markov Decision Process formulation. These algorithms does not derive the policy to be used with regards to the reward function of the Markov Decision Process, instead they have policies corresponding to a charging behaviour that is of interest for comparison. For example, one of these baseline charging algorithms in the simulations has a policy defined as following how charging of electric vehicles often is carried out today in the real world. By comparing the intelligent charging algorithm to this regular way of charging the possible gains from changing the way it is performed today can be evaluated.

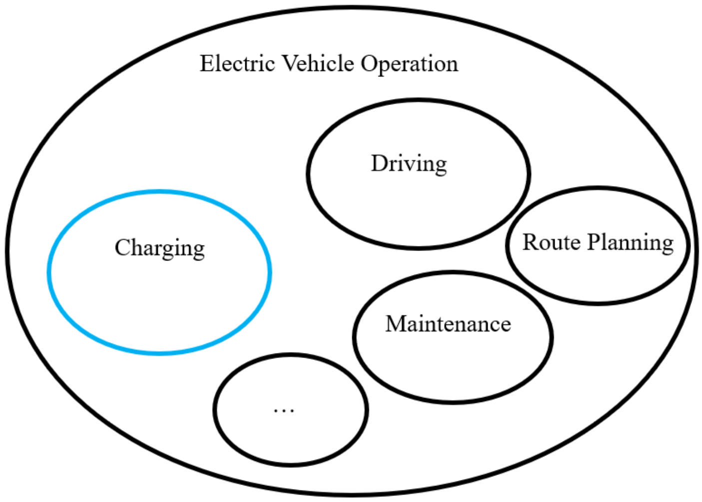

Figure 3.1: *Where the contributions of this thesis exist within the world of electric vehicle operation, marked as blue/light circle. Consequently the simulations consist of modelling and simulating charging operations.*

Multiple charging sessions with different circumstances will be simulated in order to be able to make more generally applicable conclusions. These simulations will be independent, results or state from one simulation will not affect other simulations, meaning the end results of one simulation will not affect the next or any other.

3.1.1 Operational Constraints

The operational constraints of the charging session will be defined as consisting of:

- Arrival time.
- Departure time.
- Initial State of Charge.
- Target State of Charge to be reached upon reaching the departure time.

The initial State of Charge will in simulations be set to 10%, and the target to 90%. It is assumed that the vehicle can charge at any time between the arrival time and departure time, this is said to be the *charging window*. It is for the time spent in this window the simulated charging algorithms will operate.

Even if all of the charging window is not used for charging, the simulations will still perform calculations throughout on the other areas that the charging window is said to consist of, such as the battery degradation that is defined in Section 3.1.3.

An example is the charging method called *regular*, that is described in section Section 3.3.1, that charges the battery as fast as possible. Being done in terms of charging early in the charging window henceforth implies that battery degradation will continue to affect cost throughout the rest of the time until time of departure.

The arrival and departure times used in the simulations will be chosen to be limited to two days in April 2020. These real days are chosen in order to be able to use real price data, the price region for the days is chosen to be region 3, the southern middle part of Sweden. This region includes Stockholm. The first day, 2020-04-02 is chosen for its low variations in electricity price. The prices stay between 4 and 6 öre SEK/kWh throughout the day. 2020-04-09 is the other day that is chosen, because of its high variations in electricity price. The peak price is above 30 öre SEK/kWh while the lowest is 5 öre. See Figure 3.2. For the complete specification of the charging windows being simulated see Table 3.5.

In this thesis it will be assumed that the variations of the electricity price are known from beforehand, and that the price changes at the turn of each hour. This corresponds to the electricity trading market in Sweden. However, this does not mean that all customers buying electricity buys according to that model, power companies can offer their electricity according to other payment models even if they themselves buy electricity according to the changing price of the trading market.

The charging algorithms of this thesis described in Section 3.3 make their decisions in time steps throughout the charging window. It is assumed that the electricity price does not vary within a time step. For more information on the time steps see Section 3.2.1.

3.1.2 Battery Specification

There are several parameters that need to be set in the modelling of the battery in the simulations of this thesis. The first one is the setup of the battery packs and cells. See Figure 3.3 for how cells and packs commonly relate to each other in a vehicular battery system. It will be assumed that a battery pack consist of a total of 180 cells in series, each cell with a resistance R of $1.5m\Omega$. It is assumed that the resistance is constant, and does not change with for example

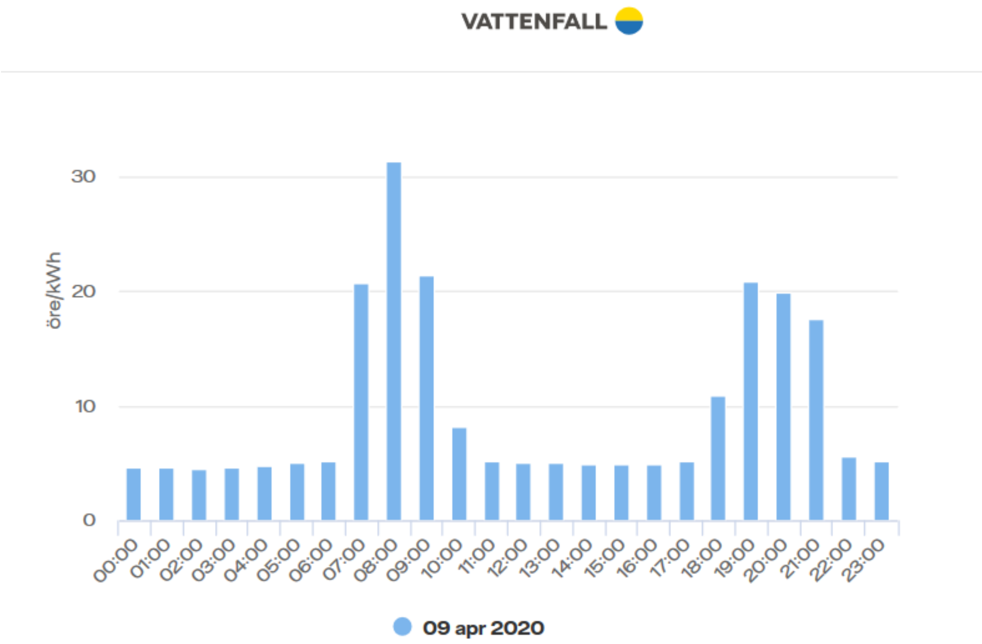

Figure 3.2: *Price data of region 3 in Sweden, 9th of April 2020. Data from Vattenfall [6]. This day is chosen to perform simulations on due to its large variations in electricity price.*

changes in State of Charge. This makes for resistance of $270m\Omega$ per pack. 10 of these packs are assumed to be mounted in parallel, see Figure 3.3, together making up the total battery unit. It will be assumed that one pack has the capacity of $50Ah$, making for a total capacity of $500Ah$ for 10 packs.

The voltage in the battery will be modelled as varying throughout a charging session, it will vary with the State of Charge of the battery. It will also vary with the resistance and the current of charge or discharge, I. The variation of the so-called Open Circuit Voltage (OCV) in a single battery cell with respect to State of Charge is assumed to follow the values of Table 3.1 and Table 3.2. To calculate the actual voltage U the following OCV formula is used:

$$U = OCV + RI \tag{3.1}$$

The State of Charge of the battery in the model will be limited between 10% and 90%, in the simulations currents from the charger that lead to violations of this will have severe effects on the reward, see Section 3.2.5.

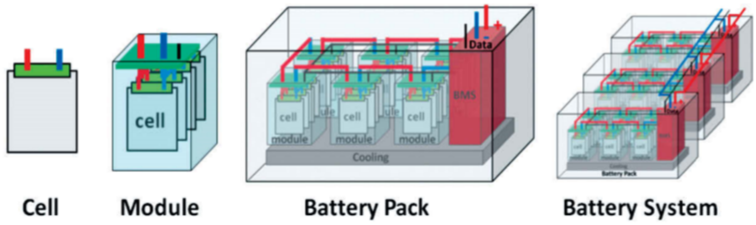

Figure 3.3: *"Hierarchy of different packaging levels of a typical battery system", Otto et al. [57].*

Table 3.1: *Open Circuit Voltage values, single battery cell, for State of Charge values of 0 to 50%.*

SOC (%)	0	5	10	15	20	25	30	35	40	45	50
Voltage (V)	3.20	3.41	3.44	3.50	3.55	3.58	3.60	3.61	3.63	3.65	3.68

3.1.3 Battery Degradation

In this thesis the battery degradation will be said to consist of capacity loss – it is assumed that capacity loss is what ultimately constitutes End Of Life of the battery. It is assumed that there are two causes to this capacity loss – cyclic ageing and calendar ageing. More specifically, capacity loss from some amount of cycling of the battery with different C-rates as well as capacity loss from the battery being in a certain State of Charge for some amount of time. It will be assumed that End Of Life of a battery consist of a loss of 20% of the original capacity, and that a monetary cost is associated with taking the battery to End Of Life. Data from Sun, Saxena, and Pecht [58] and Sun et al. [59] will be used to derive the two degrading factors – cyclic ageing and calendar ageing. See Figure 3.4 and Figure 3.5 as well as Table 3.4 and Table 3.3.

Battery Degradation from Calendar Ageing

The calendar ageing considered in this thesis will be the degradation associated with State of Charge, more specifically from a battery being in a certain State of Charge for some amount of time.

The degradation values after 900 days of storage in different State of Charge values is used from Sun, Saxena, and Pecht [58], see Figure 3.4 and Table 3.3. The data from [58] is presented for different temperatures of the battery, 25°C, 40°C and 60°C. It will be assumed that the battery always is at 25°C and hence-

Table 3.2: *Open Circuit Voltage values, single battery cell, for State of Charge values of 55 to 100%.*

SOC (%)	55	60	65	70	75	80	85	90	95	100
Voltage (V)	3.73	3.77	3.82	3.87	3.92	3.98	4.04	4.10	4.16	4.23

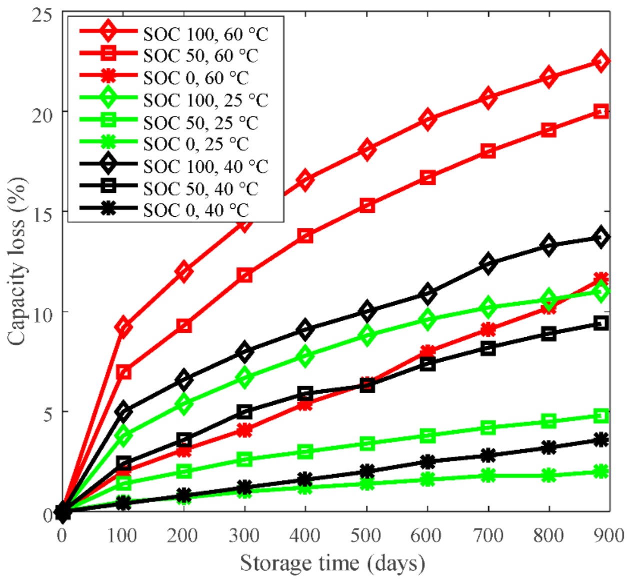

Figure 3.4: *Graph from Sun, Saxena, and Pecht [58] showing how spending time in different State of Charge values affect the calendar ageing, capacity loss. This data is used in the method presented here.*

forth the State of Charge degradation data for 25°C is used.

The complete formula for State of Charge degradation can be seen in (3.2), where $\deg_{900}$ represents the data of Table 3.3 and SOC is the State of Charge. It is assumed that for the State of Charge values between 0%, 50% and 100% the degradation scales linearly.

Table 3.3: *Capacity loss from 900 days spent in different State of Charge values. Data from Sun, Saxena, and Pecht [58]. See Figure 3.4.*

State of Charge	0%	50%	100%
Capacity loss	2%	5%	11%

$$\text{cost}(SOC, seconds) = \left(\frac{\left(\frac{\deg_{900}(SOC)}{900 \times 24 \times 60 \times 60} \right) seconds}{20\%} \right) EOL_{cost} \quad (3.2)$$

Battery Degradation from Cyclic Ageing

Data on battery degradation coming from charging with different C-rates is taken from Sun et al. [59], see Figure 3.5. This is the cyclic ageing that is considered in this thesis. From Figure 3.5 the fitted number of cycles required to reach a capacity loss of 20% is used, which results in Table 3.4.

Table 3.4: *Number of cycles of a battery required to reach End Of Life, a capacity loss of 20%, for different C-rates. Data from Sun et al. [59]. See Figure 3.5.*

C-rate	0.5C	1C	2C	3C	4C	5C
Cycles to reach End Of Life	4000	2875	2000	1250	875	750

It is assumed that the cycles required to reach End Of Life at 20% capacity loss for C-rates between the rates in Figure 3.5 scales linearly. If x cycles are charged with a certain C-rate, and charging with that rate requires c cycles to reach End Of Life of the battery with a corresponding cost of e, it is assumed that the resulting degradation cost is calculated as:

$$\text{cost} = \left(\frac{x}{c} \right) e \quad (3.3)$$

In this thesis it is assumed that the degradation from C-rate only happens when the battery is charged. Discharge currents will hence not contribute to any degradation.

3.1.4 Electrical Losses

Not all the energy coming from the charger will end up in the batteries, and vice versa in the case of Vehicle-to-Grid, due to electrical losses along the way. The formula for electrical losses is:

$$E_{loss} = I^2 Rt \quad (3.4)$$

Where I is the current, R is the resistance and t is the time in seconds. For more details on these variables see Section 3.1.2. Electrical losses will be

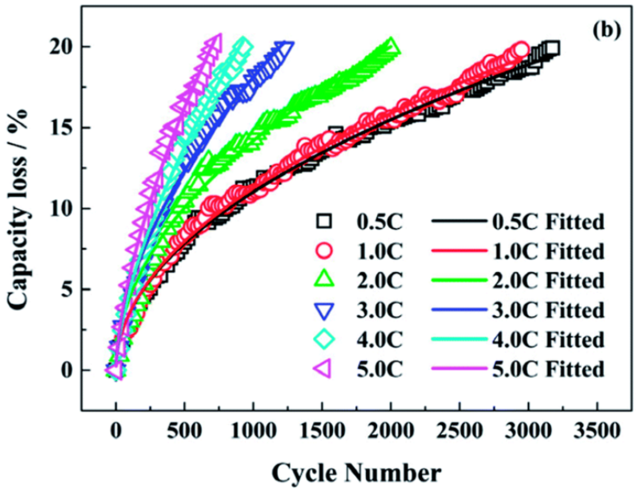

Figure 3.5: *Graph from Sun et al. [59] showing how cycling a battery affects the cyclic ageing, capacity loss. This data is used in the method presented here.*

considered in the model, for both charging and discharging with Vehicle-to-Grid. The electrical losses will affect the difference of energy flow between the charger and the battery. When charging, electrical losses will cause some of the energy coming from the charger being lost along its way the the battery. Since the energy leaving the charger is what is needed to be paid for, this effectively means that some of the energy paid for will never reach the battery. In the case of Vehicle-to-Grid it is the other way around – when the vehicle sells energy it will get paid for less energy than is released from its batteries back to the grid.

3.1.5 Chargers

The chargers simulated in this thesis will be limited by the maximum current possible. Simulations will consider situations where Vehicle-to-Grid is available, and when it is not. In the case of Vehicle-to-Grid the payment for selling electricity is assumed to be derived from the same electricity price as for buying. Furthermore, when Vehicle-to-Grid is enabled the minimum current available for discharge is assumed to be as large as the maximum current. It will be assumed that the charger can deliver all currents within the limits in all circumstances, even as the battery voltage is high and actual the power delivered will be higher. As an example, given a voltage of $750V$ and a current of $200A$ the charger will hence provide a charge power of $150kW$.

3.2 Markov Decision Process Formulation

Three different charging algorithms will me modelled in this thesis. What they all have in common is that they will be modelled using the same structure of Markov Decision Process. The setup of this Markov Decision Process is described in this section. More information on the different charging algorithms and how they make use of the Markov Decision Process will follow in Section 3.3. Theory on Markov Decision Processes can be found in Section 2.7.

3.2.1 Time

The time from when the vehicle arrives until the departure time, the charging window, will be discretized into a number of time steps. See Section 3.1.1 for more details on the charging window.

The first decision epoch will be t_{start}, when the vehicle can make its first decision on what current to use for charging. The next time the vehicle can make a decision will be at time $t_{start} + t_{step}$. Time continues to move forward with t_{step} until t_{end} is reached. The actual values for the starting time, the step size and the ending time will vary depending on simulation scenario, see Section 3.3.4.

While the actual arrival time will be variable it will still always be modelled as follows in the Markov Decision Process:

$$T := \{t_{start},\, t_{start} + t_{step},\, t_{start} + 2t_{step},\, t_{start} + 3t_{step},\, \dots,\, t_{end}\} \tag{3.5}$$

3.2.2 State Space

The state space will be formulated as the State of Charge of the vehicle. The values of the State of Charge will be discretized into finite points between 0% and 100% State of Charge, or more specifically between 0 and 1. A state will consist of being in one of these points within the discretization.

$$S := \{0,\, 0 + SOC_{step},\, 0 + 2SOC_{step},\, \dots,\, 1\} \tag{3.6}$$

The voltage of the batteries will not be part of the state space. Given the State of Charge, and the charging current, the voltage will be able to be calculated using the model defined in Section 3.1.2. The electricity price will not be encoded as being part of the state space, but will rather be wholly encoded within the reward signal, that in turn depends on the time. More information on the reward signal follows in Section 3.2.5.

3.2.3 Action Space

The action space is defined as the available charging- and discharging currents. The possible currents will be evenly spaced between the maximum capability of the charger and the minimum. This minimum can be negative, depending on if the charger has Vehicle-to-Grid enabled.

$$A := \{I_{min},\ I_{min} + I_{step},\ I_{min} + 2I_{step},\ \dots,\ I_{max}\} \tag{3.7}$$

3.2.4 Transition Probabilities & Transitions

The Markov Decision Process formulated here will be deterministic, there will never be more than one state possible as a next state for a given action. In other words, $p(s'|s, a)$ will be 0 for all s' except for one single state where it will be 1.

Since the state space is not continuous there are a limited amount of State of Charge values that can be represented. When calculating the transition from one state to another, the new state is decided by rounding to the closest possible state within the state space if needed.

3.2.5 Reward Signal

The reward signal of the Markov Decision Process will consist of the costs associated to charging. These costs are said to be:

- Costs from buying electricity to charge the battery with, $C_{Electricity}(s, a)$.
- Costs from calendar ageing of the battery, $C_{SOC}(s, a)$.
- Costs from cyclic ageing of the battery, $C_{Crate}(s, a)$.

For each action taken within the charging session these costs will be calculated, and constitute the immediate reward the agent in the Markov Decision Process sees. The above costs will be in actual SEK. The optimal policy of this Reinforcement Learning problem will hence be the one that minimises costs of these factors for the charging session – or in other words: maximises the reward.

An addition to the reward signal will be made when the action a leads to states that are not allowed. In other words, when the charge current cannot be applied without the battery State of Charge ending up outside its lower and upper limits. This cost will be fixed and set to -10 000, see (3.9).

In order to make the optimal policy consist of actions that actually perform some charging another punishment for undesired behaviour need to be added. This punishment corresponds to the deviation from the desired State of Charge as the charging session ends. Without this the cheapest way to get through the episode would be to never charge at all, or possibly to only sell some electricity – without this punishment there is no motivation to take on some costs in order to reach the target State of Charge.

$$\mathrm{c}_t(s,a) = C_{Electricity,t}(s,a) + C_{SOC}(s,a) + C_{Crate}(s,a) \tag{3.8}$$

$$r_t(s,a) = \begin{cases} -10000 \\ \qquad \text{if } s' \leq SOC_{min} \text{ or } s' \geq SOC_{max} \\ -\,\mathrm{c}_t(s,a) - \gamma\big(s'B - SOC_{target}B\big)^2 \\ \qquad \text{if } t+1 = t_{end} \\ -\,\mathrm{c}_t(s,a) \\ \qquad \text{if } t+1 \neq t_{end} \end{cases} \tag{3.9}$$

The term B in (3.9) stands for the battery capacity in Ah. Hence $s'B$ represent the Ah within the battery at state s'. $SOC_{target}B$ represents the target Ah to reach as the charging session ends. γ, which is called a *range anxiety factor* in Wan et al. [54], will be set to 0.00001. If γ is seen as being measured in SEK/Ah the range anxiety term will have the same measurement unit as the charging cost term.

3.3 Charging Algorithms

Three charging algorithms will be modelled in this thesis. The algorithms are described in this section, and are called as follows: *regular* charging, *mean* charging and *intelligent* charging. For more details on how the evaluation of the algorithms will be carried out see section Section 3.5.

3.3.1 Baseline Charging Algorithm - Regular Charging

The regular charging algorithm will be modelled to follow how charging of electric vehicles is regularly carried out in reality, hence its name. Charging with this algorithm will lead to the vehicle requesting the maximum possible current from the charger. This continues until the battery is full.

As described in Section 3.1.1 the algorithms always considers the whole charging window. This means that even when the vehicle is fully charged and there is time left until departure time the simulations will continue to calculate battery degradation. This is especially relevant considering battery degradation from calendar ageing, being fully charged early within the charging window means spending more time in high State of Charge values later.

Policy

The policy of this charging algorithm, π_r, will not be derived from any Reinforcement Learning solution methods. As said it will follow how charging is regularly performed in the real world today. Due to this the algorithm will neglect the reward signal of the Markov Decision Process formulation, since it does not choose action with regards to any rewards but rather to simply get fully charged as fast as possible. Note that even if the rewards are not considered in deriving the policy, rewards will still be logged as the algorithm is simulated, see Section 3.5. In terms of the Markov Decision Process described in Section 3.2 this algorithm takes the action that corresponds to the largest charging current in the Markov Decision Process for all time steps as long as the target State of Charge will not be overshot. If the target State of Charge is about to be overshot, it will take the action that corresponds to ending up being closest to the target.

Algorithm 1 Calculate the policy π_r for regular charging. Finds the largest charge current possible from charger without overshooting the battery target State of Charge.

```
procedure POLICY(time,battery,charger)
    ampere ← ∅
    for a ∈ charger.currents do
        soc ← battery.charge(a)
        if soc ≤ battery.target_soc then
            ampere ← a
        end if
    end for
    return ampere
end procedure
```

3.3.2 Baseline Charging Algorithm - Mean Charging

The objective of this algorithm is to find a current to charge with for the *whole* charging window in order to just reach the target State of Charge by the end.

In order for this algorithm to be able to reach the target State of Charge just in time the choice of charging current will need to be accurate. Because of this the action space as described in Section 3.2.3 will need fine discretization between the lower and upper limits of charger currents. Due to this the mean charging algorithm will always be simulated as having a large action space of 2000 possible actions between the charger limits.

Policy

The policy for the mean charging algorithm consists of choosing an action that makes the battery reach its target State of Charge right as it is time to leave. To derive this policy π_m all possible actions are tried, and the whole episode is carried out with that action constituting the whole policy π_m. The policy that leads to smallest difference to the target State of Charge at the end will be chosen as the final π_m. See Algorithm 2.

Algorithm 2 Calculate the policy π_m of the mean charging algorithm. For all currents possible from the charger, the action space, go through the whole episode with that current in order to find the one which minimises the difference between the battery State of Charge and the target as the charging session is over.

procedure POLICY(time,battery,charger)
    diff $\leftarrow \infty$ ▷ Initialise difference
    ampere $\leftarrow \emptyset$ ▷ Initialise ampere
    for a $\in$ charger.currents **do**
        battery.reset()
        for t $\in$ T **do**
            battery.charge(a)
        end for
        if |battery.soc - battery.target$_{soc}$ | < diff **then**
            ampere $\leftarrow$ a
            diff $\leftarrow$ |battery.soc - battery.target$_{soc}$ |
        end if
    end for
    return ampere
end procedure

3.3.3 Charging Algorithm - Intelligent Charging

The intelligent charging algorithm will derive its policy using dynamic programming, utilising the reward signal described in Section 3.2.5. This way the policy π_i will be the one that maximises the reward signal, which will correspond to the policy that minimises the cost of electricity and degradation – as well as accurately achieving the targeted State of Charge.

Since there are only one possible next state from being in a state and choosing an action in the Markov Decision Process formulation, the time complexity of the algorithm mentioned in Section 2.7 will be slightly changed.

Algorithm 3 Dynamic programming algorithm [52] to find the optimal state-action value function u.

```
procedure DynamicProgramming(time,battery,charger)
    u ← ∅^{T×S×A}
    for t ∈ {t_end − 1 ... 1, 0} do
        for s ∈ battery.states do
            for a ∈ charger.currents do
                t', s' ← charge(t,s,a)
                u[t,s,a] = reward(t,s,a) + max_a(u[t',s'])
            end for
        end for
    end for
    return u
end procedure
```

Policy

The policy of the intelligent charging algorithm will consist of choosing the action of the value function with the maximum value. See Algorithm 4.

Algorithm 4 The policy π_i for intelligent charging algorithm.

```
procedure Policy(time,state,u)
    ampere ← argmax_a(u[time,state])
    return ampere
end procedure
```

3.3.4 Simulation Group 1 - Electricity- & Battery Cost

The first group of simulations in this thesis will be performed in order to capture differences in electricity price and battery End Of Life cost. From this the hope is to be able to draw conclusions on the differences between the charging algorithms from a more general standpoint, to not have the results and corresponding discussion be based upon the the outcome of a specific situation but and instead be able to draw more general conclusions that can hold overall. These simulations will be performed with a charging window size of 7 hours, see Table 3.5 for a table of all simulations. This is believed to be a reasonable compromise between probable real-world scenarios. Some of these scenarios include charging between operations during the day, charging over the night and scenarios where vehicles are operated in two-shift or three-shift. The charger will here be assumed to be capable of 200A. All simulations will be ran twice, one where the charger is assumed to have Vehicle-to-Grid enabled, and one time where it is disabled.

Table 3.5: *Operational constraints specifying the arrival times, departure times and the charging windows for the different price-capturing simulations. These operational constraints will be combined with the different battery specifications seen in Table 3.6.*

Date	Charging Window	Duration	State of Charge Target
2020-04-02	05:00 - 12:00	7h	10% → 90%
2020-04-02	06:00 - 13:00	7h	10% → 90%
2020-04-02	07:00 - 14:00	7h	10% → 90%
2020-04-02	08:00 - 15:00	7h	10% → 90%
2020-04-02	09:00 - 16:00	7h	10% → 90%
2020-04-02	10:00 - 17:00	7h	10% → 90%
2020-04-09	05:00 - 12:00	7h	10% → 90%
2020-04-09	06:00 - 13:00	7h	10% → 90%
2020-04-09	07:00 - 14:00	7h	10% → 90%
2020-04-09	08:00 - 15:00	7h	10% → 90%
2020-04-09	09:00 - 16:00	7h	10% → 90%
2020-04-09	10:00 - 17:00	7h	10% → 90%

The 7h-simulations will be ran with different costs associated to End Of Life of the battery units. These cost hence constitute taking the batteries to a 20% capacity loss, and may or may not be the full production cost of the batteries depending on their worth at End Of Life. See Table 3.6 for a full specification of the two types of battery units used in simulations. See Section 3.1.2 for more details on the specification of the batteries.

Table 3.6: *The specification of the two battery units that will be used in simulations – differing in the cost that is associated to taking the units to End Of Life.*

Battery	End Of Life cost	Capacity	Packs	Resistance per pack
Unit 1	1 000 000 SEK	$500Ah$	10	$270m\Omega$
Unit 2	100 000 SEK	$500Ah$	10	$270m\Omega$

These simulations use a 300 seconds (5 minutes) discretization of the time within the Markov Decision Process, meaning a new action can be chosen every 5 minutes. The State of Charge values will be discretized into 1000 steps, there are 1000 possible State of Charge values the battery in the model can be in. The charger currents will be discretized into steps of 10A. As stated in Section 3.3.2 the mean charging algorithm will need a larger discretization, when running the algorithm its action space will consist of 2000 possible actions between the charger limits.

3.3.5 Simulation Group 2 - Session Duration, Costs & Chargers

This group of simulations will be performed in order to capture how differences in charging session duration, battery End Of Life costs and charger capabilities affect the performance of the charging algorithms. Again the two dates described in Section 3.1.1 will be used, 2020-04-02 and 2020-04-09. All simulations within this group will have the time discretized into steps of 600 seconds, 10 minutes. The action space, the possible charging currents, will be discretized with steps of 10A between the charger limits. The values for State of Charge possible within the Markov Decision Process, the state space, will be discretized into 1000 values.

The first batch of simulations will be ran on 2020-04-02 and will vary the charging session duration together with the battery End Of Life cost. The charging sessions will start at 05:00 and run with lengths varying from 2 hours to 12 hours. The battery End Of Life costs will vary from 100 000 SEK to 2 000 000 SEK. The charger will be set to $200A$, and Vehicle-to-Grid will be enabled. The capacity, the number of packs in the battery and the resistance will be modelled the same as in Section 3.3.4, the battery will be assumed to consist of 10 packs, with a total capacity of $500Ah$ and a resistance per pack of $270m\Omega$. See Table 3.7.

Table 3.7: *Operational setup and battery End Of Life cost for the first batch of simulations within Simulation Group 2. The simulations will be ran with varying battery End Of Life cost and varying charging window duration.*

Date	2020-04-02
Charging Window	05:00 - Varying
Battery End Of Life cost	Varying
State of Charge Target	10% $\rightarrow$ 90%

The second group of simulations will take place on 2020-04-09 and will have the charger capabilities and the battery End Of Life cost varying. The charger capability will go from 200A to 1000A. The battery End Of Life costs will vary from 100 000 SEK to 2 000 000 SEK. The charging session duration will be set to 7 hours.

Table 3.8: *Operational setup and battery End Of Life cost for the second batch of simulations within Simulation Group 2. The simulations will be ran with varying battery End Of Life cost and varying charging capabilities.*

Date	2020-04-09
Charging Window	05:00 - 12:00
Battery End Of Life cost	Varying
Charger capability	Varying
State of Charge Target	10% $\rightarrow$ 90%

3.4 Software

The program will be written in Python using the numerical library NumPy [60]. The software will be ran on a Windows 10, 64 bit Intel Core i7 16GB RAM laptop. In order to be able to efficiently aggregate results several parameters will be able to be specified when running the program, as inputs. See Listing 3.1.

```
for /l %%x in (5, 1, 10) do (
   python main.py --date=2020-04-09 --start_hour=%%x
)
```

Listing 3.1: *Windows batch script to aggregate results with different values specified for parameters, in this example the starting hour.*

For a given setting of the environment variables, the baseline algorithms as well as the proposed intelligent charging algorithm will be simulated, each generating its corresponding output data and images.

3.5 Evaluation

The battery degradation data used in this thesis, described in Section 3.1.3, will be evaluated in terms of what the implications are on actual battery usage, when there is a cost associated to the battery. The battery degradation due to calendar ageing will be evaluated in terms of what it costs to have a battery be in a certain State of Charge for some amount of time. The degradation on the battery due to cyclic ageing will be evaluated as to see what it costs to cycle the battery for certain C-rates.

The regular charging and mean charging algorithms will be used to evaluate the performance of the intelligent charging algorithm, how much cost that can be saved by charging when taking electricity price and battery degradation into account.

The costs (not plainly the reward signal, since it is pseudo-monetary in the sense that it also contains punishments that are not actual costs that can be experienced) will be monitored and logged for each decision epoch in the simulations. The cost will be broken down into its components, cost from buying- or selling electricity and costs from battery degradation broken down into the two components cyclic degradation and calendar degradation. Throughout the charging window the voltage, State of Charge, charge current and C-rate will be logged.

At the end of the charging sessions the accumulated total cost will be evaluated for the three charging algorithms, and the cost of the intelligent charging algorithm will be compared against the other algorithms.

Graphs will be generated from the data logs in order to be able to evaluate the decisions made throughout a charging session, and put them in context of the electricity price and current voltage.

Chapter 4

Results

This chapter describes the findings of this thesis, from the results of the chosen model of batteries and battery degradation to how the different charging algorithms performed in the various simulations.

4.1 Voltage Model

From the specification of the battery in Section 3.1.2, specifically the specification of voltage per battery cell, the voltage of Figure 4.1 is achieved for a full battery unit. It can be seen that the voltage changes as the State of Charge increases. It can also be seen that the voltage increases or decreases slightly depending on the charging current.

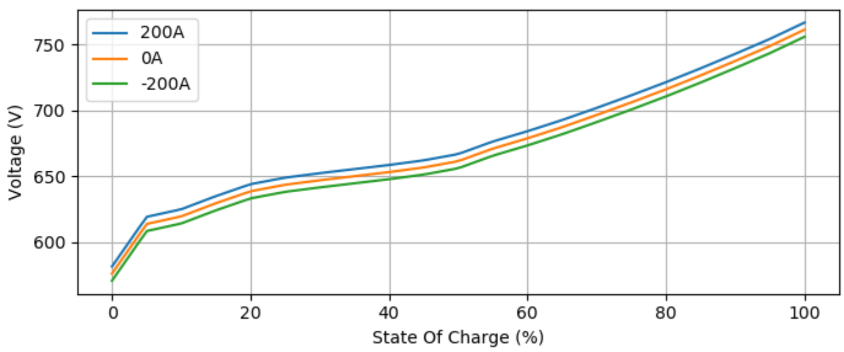

Figure 4.1: *Voltage for the 10 pack battery used in simulations, for different State of Charge-values and currents of* $-200A$ *and* $200A$*.*

From the battery degradation model the costs of calendar ageing, cost of being in a certain State of Charge for some time was derived as seen in Figure 4.2. Staying in 80% State of Charge for 1 hour, with the 100 000 SEK battery used in simulations costs approximately 2 SEK, with the 1 000 000 SEK battery making for a cost of 20 SEK.

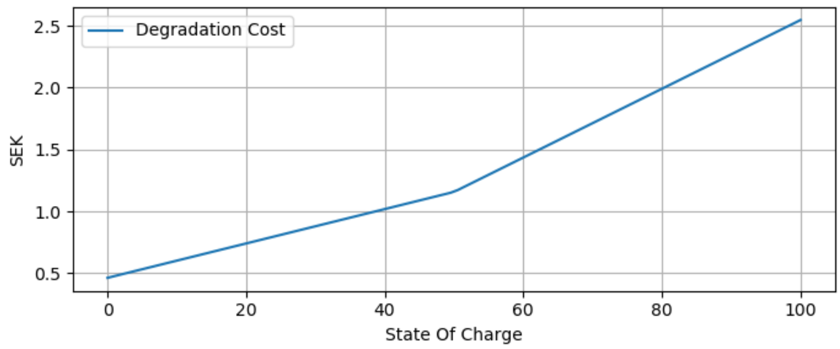

Figure 4.2: *Degradation cost associated with being in a State of Charge for 1 hour, for the battery unit with cost 100 000 SEK used in simulations.*

Another result from the degradation model is the cost from cyclic ageing, the cost associated with cycling the battery for different C-rates. See Figure 4.3. One full cycle of the 100 000 SEK battery used in simulations with a C-rate of 3 cost around 80 SEK. For the battery with cost of 1 000 000 SEK the corresponding cost is instead 800 SEK.

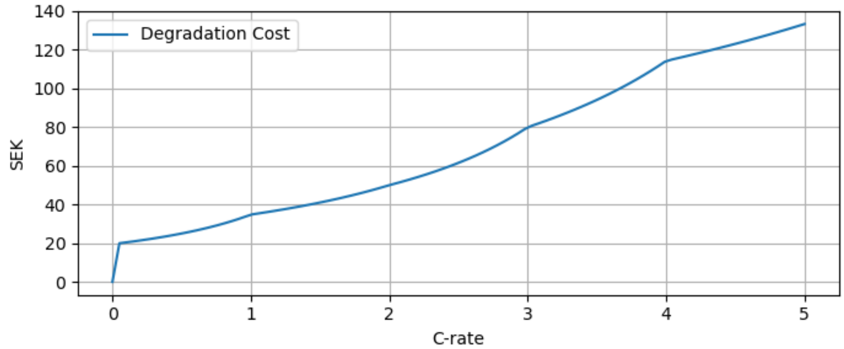

Figure 4.3: *Degradation cost associated with charging a full cycle of the 100 000 SEK battery used in simulations for C-rate.*

4.2 Simulation Group 1

Assuming a voltage of 700V, the 500Ah battery costing 1 000 000 SEK has a cost of around 3000 SEK/kWh. The 100 000 battery has a cost of 300 SEK/kWh.

The results from simulations show that the intelligent charging algorithm effectively can reduce the charging costs. For the 100 000 SEK battery on 2020-04-09 intelligent charging had an average of 63.5% lower costs compared to regular charging, with savings of 46 SEK. On 2020-04-02, the day with a flatter electricity price, the average cost saving compared to regular charging was 11 SEK.

Table 4.1: *A duplicate of Table 3.7, to highlight how the simulations were ran and put the results in context. Operational constraints specifying the arrival times, departure times and the charging windows for the different price-capturing simulations. See Section 3.3.4.*

Date	Charging Window	Duration	State of Charge Target
2020-04-02	05:00 - 12:00	7h	10% → 90%
2020-04-02	06:00 - 13:00	7h	10% → 90%
2020-04-02	07:00 - 14:00	7h	10% → 90%
2020-04-02	08:00 - 15:00	7h	10% → 90%
2020-04-02	09:00 - 16:00	7h	10% → 90%
2020-04-02	10:00 - 17:00	7h	10% → 90%
2020-04-09	05:00 - 12:00	7h	10% → 90%
2020-04-09	06:00 - 13:00	7h	10% → 90%
2020-04-09	07:00 - 14:00	7h	10% → 90%
2020-04-09	08:00 - 15:00	7h	10% → 90%
2020-04-09	09:00 - 16:00	7h	10% → 90%
2020-04-09	10:00 - 17:00	7h	10% → 90%

The average savings for a charging session when comparing intelligent to regular charging for the 1 000 000 SEK battery was approximately 30% for both days, with savings larger than 100 SEK. The average savings for 2020-04-09, the day with varying price, was 123 SEK. The mean charging algorithm achieved lower costs on average compared to regular charging. It could occasionally be seen to have a slightly higher cost, as seen in Figure 4.4. Using the intelligent charging algorithm compared to using mean charging had an average cost improvement of 29.9% for the 100 000 SEK battery. The average improvement for the 1 000 000 SEK battery was 11.6% lower costs.

Table 4.2: *100 000 SEK battery average costs for all algorithms, over all of the 7h simulated charging sessions for the two dates, see Table 4.1.*

Date	**Algorithm**	**Avg. Cost**	**Savings, Intelligent**
2020-04-09	Intelligent	26 SEK	-
2020-04-09	Mean	54 SEK	27 SEK (51%)
2020-04-09	Regular	72 SEK	46 SEK (63%)
Date	**Algorithm**	**Avg. Cost**	**Savings, Intelligent**
2020-04-02	Intelligent	36 SEK	-
2020-04-02	Mean	39 SEK	4 SEK (9%)
2020-04-02	Regular	47 SEK	11 SEK (24%)

Table 4.3: *1 000 000 SEK battery average costs for all algorithms, over all of the 7h simulated charging sessions for the two dates, see Table 4.1.*

Date	**Algorithm**	**Avg. Cost**	**Savings, Intelligent**
2020-04-09	Intelligent	245 SEK	-
2020-04-09	Mean	283 SEK	38 SEK (13%)
2020-04-09	Regular	368 SEK	123 SEK (34%)
Date	**Algorithm**	**Avg. Cost**	**Savings, Intelligent**
2020-04-02	Intelligent	242 SEK	-
2020-04-02	Mean	268 SEK	26 SEK (10%)
2020-04-02	Regular	343 SEK	101 SEK (29%)

It could be observed that Vehicle-to-Grid was only used by the intelligent charging algorithm in the case of the less expensive 100 000 SEK battery, and then only on the day 2020-04-09 – the day with large variations in electricity price. An example of Vehicle-to-Grid being used can be seen in Figure 4.4. This results in there being a cost saving implication to using Vehicle-to-Grid only in the case of 100 000 SEK battery on 2020-04-09, when comparing the simulations that had Vehicle-to-Grid enabled to the ones that had not. The average cost saving over all charging sessions by utilising Vehicle-to-Grid was 27%, for the less expensive battery on 2020-04-09. The total average savings from using Vehicle-to-Grid with the less expensive battery was 13.5% lower costs. See Table 4.4.

When the intelligent charging algorithm utilises Vehicle-to-Grid, selling electricity, it can reduce costs even further. As seen in Figure 4.4 the intelligent charging ends up on a total cost of 7 SEK, as compared to 61 SEK and 46 SEK for the mean- and regular charging algorithms respectively. The degradation

Table 4.4: *Cost savings from being able to utilise Vehicle-to-Grid in the intelligent charging algorithm, average over all charging sessions for the two dates and two battery unit costs.*

Battery Cost	**Date**	**Savings using Vehicle-to-Grid**
100 000 SEK	2020-04-02	0 SEK (0%)
100 000 SEK	2020-04-09	10 SEK (27%)
1 000 000 SEK	2020-04-02	0 SEK (0%)
1 000 000 SEK	2020-04-09	0 SEK (0%)

costs of the intelligent charging can be observed to be higher than the cost of the other algorithms, while the electricity costs of the intelligent charging ends up on -39 SEK.

For the simulations with the battery costing 100 000 SEK the electricity cost is the highest or close to the highest cost factor for the charging sessions, as can be observed in Figure 4.4. When the battery costs 1 000 000 SEK the simulations show that degradation costs from cyclic ageing is the largest portion of the total cost. See Figure 4.5.

4.3 Simulation Group 2

For the simulations with varying battery End Of Life costs and varying charging session duration on 2020-02-04 the intelligent charging algorithm proved to save the most money in absolute numbers compared to the regular charging when the battery was expensive and the charging session duration long. The savings was 350 SEK when the charging session duration was 12h and the battery End Of Life cost was 2 000 000 SEK. See Figure 4.6. In the same simulations the savings in percentage was the largest, see Figure 4.8.

In the simulations with varying battery End Of Life cost and varying charger capabilities on 2020-04-09 the use of Vehicle-to-Grid could be observed. Vehicle-to-Grid was only used on the less expensive batteries. When Vehicle-to-Grid was used by the intelligent charging algorithm it accounted for savings in SEK, see Figure 4.7. The savings in percentage were large, over 100% for the less expensive batteries, see Figure 4.9. The savings in SEK by using Vehicle-to-Grid in the intelligent charging was smaller than the savings that could be observed for expensive batteries and when the charger could provide high currents – in these situations was around 500 SEK.

Table 4.2 and Table 4.3, together with Figure 4.8 and Figure 4.6 show that

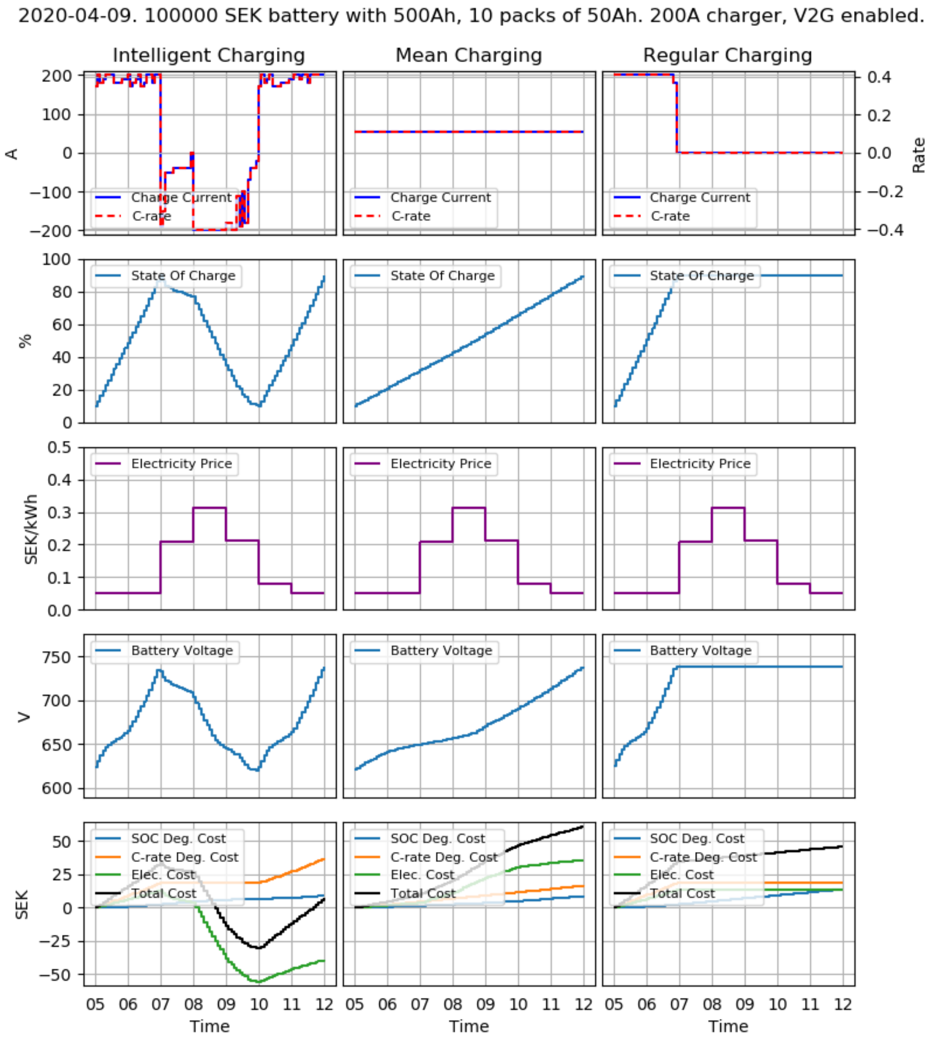

Figure 4.4: *The three charging algorithms in a simulated charging session from 05:00 to 12:00 on 2020-04-09, with the battery costing 100 000 SEK. Seen in the figure in order from top to bottom are values for charging current, C-rate, State of Charge, electricity price, voltage and cost factors. Vehicle-to-Grid is enabled by the charger, and is used by the intelligent charging.*

on a day with small changes in electricity price, 2020-04-02, the intelligent charging algorithm can save money compared to regular- and mean charging algorithms.

Intelligent charging does not use Vehicle-to-Grid to reduce costs if the battery cost more than around 500 000 SEK, or 1 500 SEK/kWh assuming a voltage of 700V.

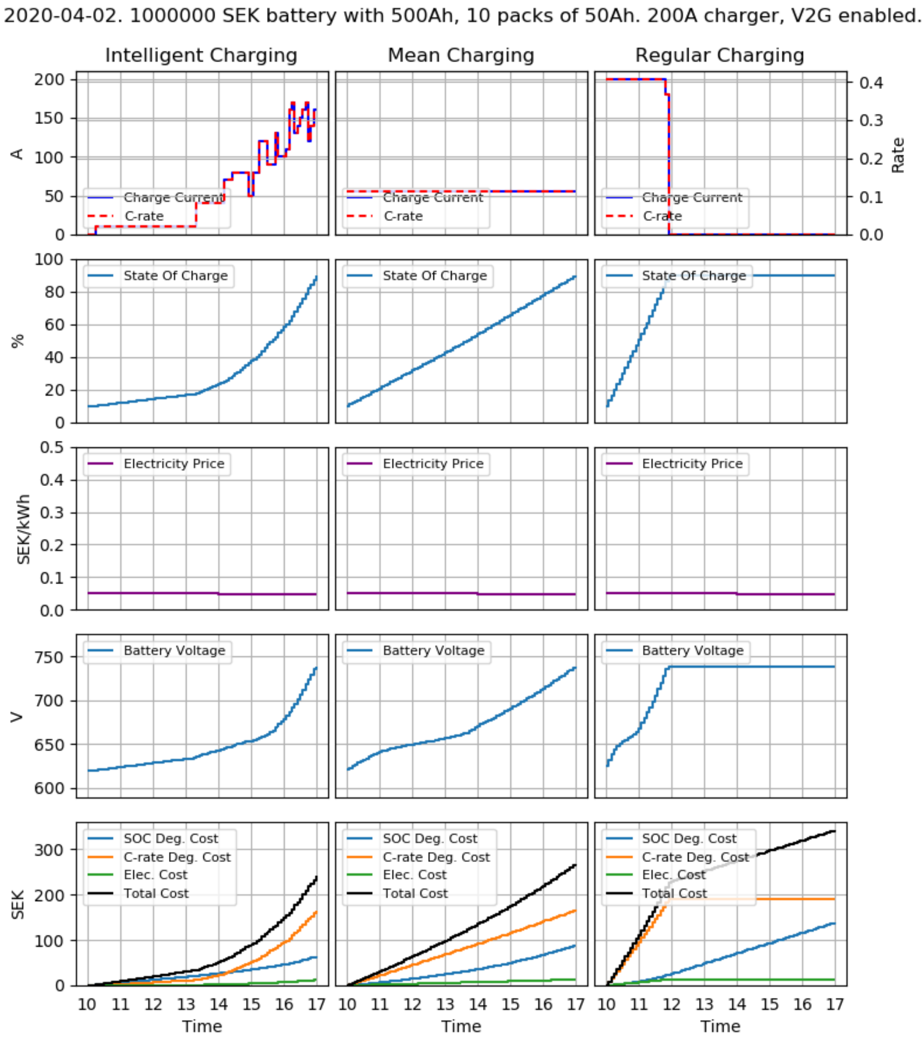

Figure 4.5: *The three charging algorithms in a simulated charging session from 10:00 to 17:00 on 2020-04-02, with the battery costing 1 000 000 SEK. Seen in the figure in order from top to bottom are values for charging current, C-rate, State of Charge, electricity price, voltage and cost factors. Vehicle-to-Grid is enabled, but never used.*

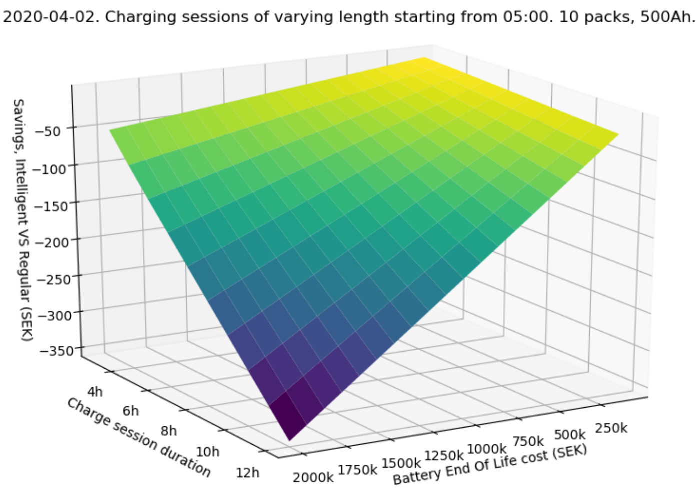

Figure 4.6: *Surface graph showing the cost savings from using intelligent charging algorithm compared to regular charging algorithm on 2020-04-02, for varying charging session lengths starting from 05:00 and for battery End Of Life costs varying from 100 000 SEK to 2 000 000 SEK.*

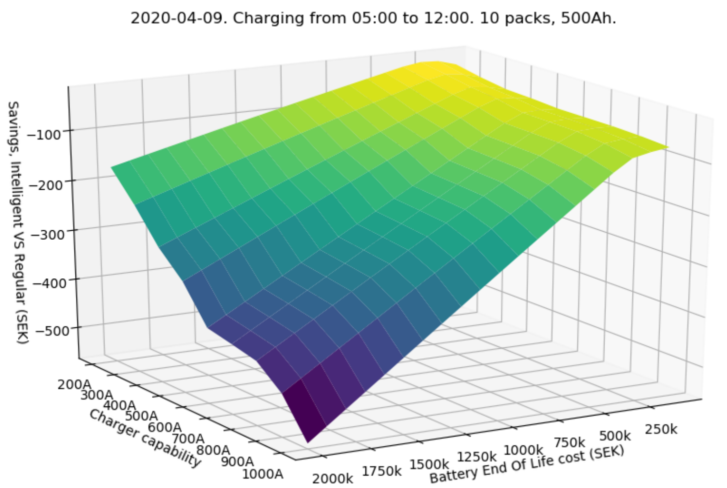

Figure 4.7: *Surface graph showing the cost savings from using intelligent charging algorithm compared to regular charging algorithm on 2020-04-09, for varying charger capabilities from 200A to 1000A and for battery End Of Life costs varying from 100 000 SEK to 2 000 000 SEK. Vehicle-to-Grid is enabled. Note the slight increase in savings for low-cost batteries due to Vehicle-to-Grid.*

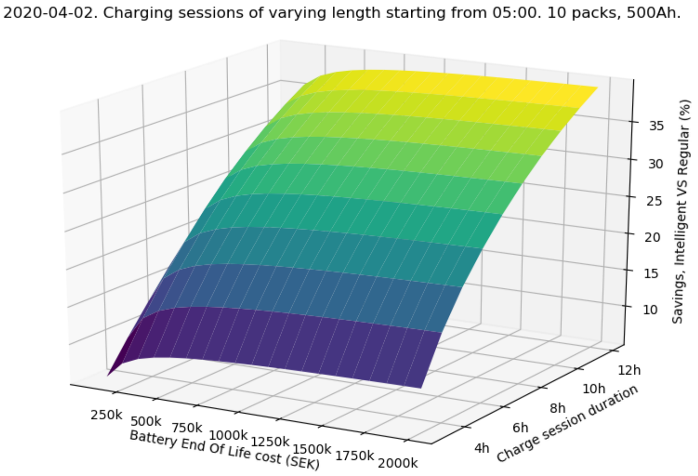

Figure 4.8: *Surface graph showing the cost savings in percentage from using intelligent charging algorithm compared to regular charging algorithm on 2020-04-02, for varying charging session lengths starting from 05:00 and for battery End Of Life costs varying from 100 000 SEK to 2 000 000 SEK.*

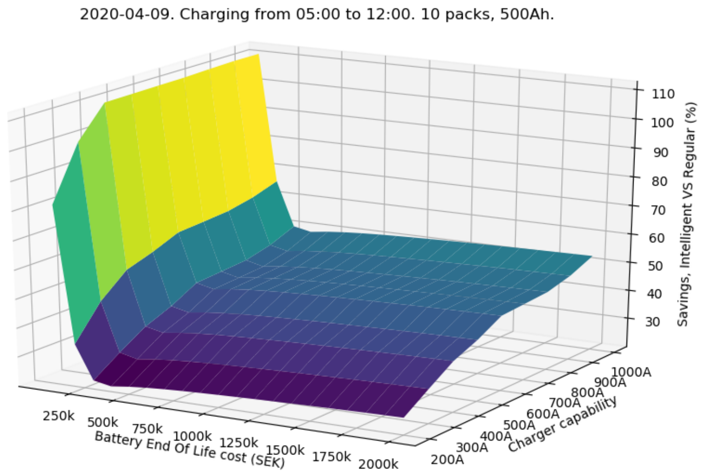

Figure 4.9: *Surface graph showing the cost savings in percentage from using intelligent charging algorithm compared to regular charging algorithm on 2020-04-09, for varying charger capabilities from 200A to 1000A and for battery End Of Life costs varying from 100 000 SEK to 2 000 000 SEK. Vehicle-to-Grid is enabled and responsible for the large savings in % for inexpensive batteries.*

Chapter 5

Discussion

This chapter discuss the findings and methods of the thesis. Possible sources of errors are introduced, and the thesis is put into the context of sustainability. Finally future work is discussed.

5.1 Reinforcement Learning

Preliminary tests using Q-learning to derive the optimal policy for the Markov Decision Process to be used by the intelligent charging algorithm of the charging sessions showed poor convergence results. This was the case for numerous different trials of different learning rates and step sizes of the Q-learning algorithm. The poor convergence of the algorithm is believed to come from certain features of the reward signal formulated in the Markov Decision Process, see Section 3.2.5. The reward signal is formulated in a way that makes the immediate reward of the last time step stand for a significant share of the total cumulative reward over a whole episode – due to the punishment in the last time step of not fulfilling the operational constraints in terms of State of Charge needed on departure. Furthermore, while the cumulative reward is largely made up by the rewards of the *last* time step, the actions in the *beginning* of an episode highly affect the end result of the charging session – namely whether or not the charging algorithm will be able to make the vehicle reach its target State of Charge. For example, choosing to not charge in the beginning of a charging session can make it impossible to reach the target State of Charge in time. This leads to extremes in terms of values of actions being affected by future rewards. The immediate rewards throughout a charging session consist of the costs of electricity and battery degradation. These immediate costs does not vary dramatically, and hence the values associated by taking different actions does not have large differences. This is in contrast to the part of the reward signal that is the punishment for not reaching the operational constraints, which is large. This punishment has to be large in order to have the optimal policy be one that satisfies the operational constraints – the punishment has to be larger than the sum of all immediate rewards (costs) throughout the *whole* episode. If the largest possible punishment dealt for deviating from the operational constraints were smaller than the total costs of charging – the optimal policy would consist of a charging strategy that does not charge *at all*, or possibly only discharge. This might seem counter intuitive. In the end, the Markov Decision Process formulation of this thesis is based around *costs*, and the goal of achieving the target State of Charge will inevitably require costs (buying electricity and degradation). The optimal policy will hence be the policy that has the lowest cost. If there is a possibility to achieve a lower cost by taking a larger penalty due to deviating from the target while at the same time having to pay less for electricity and degradation, then this will be the optimal policy. Due to this, the penalty term of the reward signal has to be sufficiently large. In turn due to this the convergence of the Q-learning algorithm on this Markov Decision Process become inefficient, it becomes difficult to evaluate actions early on in the episode from a large penalty in the end of the episode. The discount factor of the Q-learning algorithm would need to be large, in order to propagate costs further, and to emphasise the long-term reward.

Choosing to model the punishment of not reaching the desired charge within the reward signal as in [54], by having it in actual units of kWh is probably a good thing. One could model it as coming from the difference in State of Charge values, however this would lead to different scaling compared to the other parts of the reward signal, such as the electricity cost. When modelling a smaller battery, both the electricity cost and the punishment from not reaching the target would be scaled down proportionally, there will be less cost from buying electricity but also less energy-difference. Having the punishment of not reaching target in State of Charge-values would make for the same punishment independent of the battery size being modelled, even when the other parts of the reward signal would have been scaled up or down. This could lead to different results when modelling different batteries.

In [54] the voltage of the battery is not modelled. This way the energy charged/discharged with a certain current will be independent of the State of Charge the battery is in, which may make results inaccurate since the voltage, in the model used in this thesis at least, can be seen to vary significantly. See Figure 4.1 and Section 4.1.

5.2 Intelligent Charging

Seemingly unexplainable inconsistencies in the charging behaviour of the intelligent charging algorithm can be observed. The optimal policy can be seen to take actions that raise the charging current, while for the next action it lowers the current. This on its own would not be unexplainable, since for example the electricity price can go up and down – making it reasonable to have the charging current do the same. However, on some occasions the charging current is seen to vary up and down several times within the same hour – where the price is constant. See Figure 4.5. This is believed to happen for at least two reasons. The first reason being the existence of several discontinuities in the reward signal and in the model. A couple of these discontinuities exist in the voltage model. How the voltage varies with State of Charge in the model is not continuous. See Section 3.1.2 and Section 4.1. The model contains several singularities, discontinuous points. The degradation costs stemming from cyclic ageing and calendar ageing contain discontinuities as well, the values for cyclic degradation costs especially which does not scale linearly between the singular points, see Figure 4.3. Another reason is believed to be rounding errors within the dynamic programming algorithm. The computations of the algorithm include many sequential operations, making it prone to accumulated rounding errors. Several underlying data types in NumPy, such as `double` and `longdouble`, to store the floating point values of the value function were tried with similar results.

Even without being able to utilise a changing electricity price to achieve lower costs the intelligent charging proved to be more efficient than regular- and mean charging, due to the savings from charging with battery degradation in mind.

Thompson [8] claim that most electric vehicles are immobile most of the time. This might be true on average, but for commercial electric vehicles such as trucks it may not be vary accurate. Thompson continue to state that calendar ageing is the dominant reduction factor for batteries. This too might not be true for commercial electric vehicles. Although Thompson state that charging strategies should be designed to handle calendar ageing first, it is also stated that an ideal strategy should be able to balance both calendar Ageing and cyclic ageing.

In the 2017 report The Future of Trucks, from International Energy Agency [28], the term Vehicle-to-Grid is not mentioned. This can be considered to be somewhat strange, since especially commercial vehicles with their large batteries could have potential to contribute to the power grid. If the future of trucks involve electrification, as [28] mentions, there are several challenges within the electricity grid that need to be solved to support this [14, 15, 2] – challenges where Vehicle-to-Grid can be valuable [15, 40, 39, 41]. As shown in Section 4, Table 4.4 and Figure 4.4 Vehicle-to-Grid is only valuable to use in the way it is formulated in this thesis (see Section 3.1.5) when electricity prices show great variations – which may be exactly what the electricity market are moving towards since it can be beneficial for both consumers and the grid itself [23, 22]. Uddin et al. [38] even mentions that Vehicle-to-Grid can be beneficial to use since it can reduce battery degradation, for example by reduce calendar ageing by lowering the State of Charge and by that decrease the time spent in high State of Charge (which causes more battery degradation [8, 59]). Finally, from the results of this thesis it can be seen that Vehicle-to-Grid have potential to save money. The findings form this thesis that Vehicle-to-Grid is only used for charging when the battery is inexpensive corroborates the similar results of [54].

Commercial vehicles will not be available for Vehicle-to-Grid as much as passenger vehicles due to their more continuous operation, on the other hand commercial transport will be carried out in a much more planned manner than passenger transport, making for greater possibilities of a coordinated effort – possibly including intelligent charging algorithms.

5.3 Sustainability & Ethics

Batteries often contain metals and minerals that are mined using methods that cause negative impacts on the environment. If batteries cannot be efficiently recycled (or reused), saving operational costs of electric vehicles by utilising Vehicle-to-Grid can have negative environmental impacts if it reduces the life time of a battery unit.

For this to be sustainable one solution could be to enforce companies that put batteries onto the market be responsible for the recycling process. This strategy has been adopted in Sweden for the recycling of not only for example carton and plastics, but for batteries as well – companies that put these products on the market are together responsible in terms of funding for the collection and recycling process [61, 62]. Another important factor in making the use of batteries more sustainable is to have the batteries be designed from the beginning with recycling in mind, so that all batteries sold on the market have the possibility to be recycled as efficiently as possible.

The theory behind circular economy is to instead of focusing on recycling of products that have served their purpose, such as batteries that have reached

End Of Life, rather make all efforts possible to increase the lifetime of products and increase reuse [63]. This would reduce the needs for recycling, since products and components continues to be used and goes from serving one purpose to another as its current lifetime expires. Applying theories from circular economy to the use and manufacturing of batteries can be especially important, since small volumes and high cost makes for low profitability in recycling of for example lithium [64]. Stena Recycling [64] mention that it is primarily copper, nickel and cobalt that is recycled from lithium-ion batteries. It is especially important to recycle, or reuse, products that contain cobalt since violations to human rights and child labour has been reported at mining sites in Kongo, which is the largest producer of cobalt in the world [65]. SGU Sveriges Geologiska Undersökning [65] describe that most of the cobalt mines in Kongo are owned by Chinese companies which in turn raise ethical concerns. The EU have made efforts to make the union less dependent on China for cobalt, with projects involving Sweden since Sweden has one of the largest mining industries in EU [65].

An intelligent charging algorithm can contribute to keeping the batteries functional as long as possible, as Wikner [37] describes the battery lifetime in vehicles can be prolonged by better planning of the charging, without having to interfere with the driving itself.

If the intelligent charging algorithm simulated in this thesis or similar were to be implemented in reality to plan the charging of possibly numerous electric vehicles in a fleet operating daily, the computational resources needed may yield significant energy use. As stated in Dagens Nyheter [66] and Die Welt [67] the computational resources around the world amount for significant energy use – it is stated that computers and servers used for the to run and operate the internet consume as much energy as global aeroplane transportation.

Intelligent charging algorithms in reality constitutes handling data. In the case of this thesis some of this data might be sensitive. For example sending arrival times and departure times in order to calculate the optimal way of charging could potentially put privacy of a driver at risk. Extensions of the intelligent charging algorithm developed in this thesis, such as including route planning and controlling a whole fleet of vehicles may even further put privacy at risk, in part of the route planning needing locations and the fact that fleet planning may need offsite computational resources with implied sending and handling data of by third parties.

5.4 Future Work

Commercial transport companies likely operate a whole fleet of vehicles. A scenario in that case can be that multiple vehicles need to be charged together at a depot, for example during night time. In this case an intelligent charging algorithm will need to not only consider a single vehicle, but rather coordinate the whole fleet. This comes with additional challenges, for example the power grid connection to the depot might not be able to handle all vehicles charging at the same time. In that case, some degree of sequential charging may be required, which could have implications on calendar ageing, cyclic ageing and costs of buying electricity if the price varies.

In this thesis the temperature is assumed to be constant. This is likely not the case in reality, where charging batteries can generate large amounts of heat. Either this heat can be handled by on-board cooling systems on the vehicle or some heating could be tolerated. Whichever way this is solved it will lead to implications on the charging procedure – cooling systems will require extra power and by that making the charging less efficient while allowing heating of the battery will have effects on the battery degradation. Auxiliary systems in general, such as cooling of the batteries, have not been covered in this thesis. Effective control of the auxiliary systems on a vehicle is likely to be important for an intelligent charging algorithm to be applicable to real vehicles. In this thesis it has been modelled that the vehicle can decide to charge with $0A$, in other words not charge at all while still being plugged in to a charger. In reality there may be no such possibility to *"not charge at all"* while connected to a charger due to several auxiliary systems needing to be active, meaning that some current will still be drawn from the charger even if the batteries of the vehicle is not being charged. If an intelligent charging algorithm would like to wait for some time before charging the battery, for example in the scenario of a long charging session where calendar ageing need to be avoided, it may not make sense for the vehicle to have its auxiliary systems running for all that time until the actual charging begins. Including auxiliary systems in the model could hence allow for further improved solutions that are even more likely to be able to be used for real vehicles.

Not including the electricity price in the state space, but rather defining it as part of the reward signal, has some implications on the algorithm. This means that different electricity prices will not be able to be learned. A trained algorithm will only be able to output charging schedules for the price data that was used during training, it cannot output an intelligent schedule for other price variations. A possible development could include electricity prices in the learning process, and possibly even include measures of predicting unknown electricity prices.

Hybrid electric vehicles, which have small batteries, or possible future battery electric vehicles with very large battery units, may not have been captured in the simulations and studies covered in this thesis. For example, an implication of having small batteries in combination with powerful chargers can lead to high C-rates and large degradation costs from cyclic degradation. How an intelligent charging algorithms can help in reducing costs in these scenarios is yet to be studied.

Chapter 6

Conclusions

This thesis has investigated the possible gains of using an intelligent charging algorithm for electric vehicles, by formalising a charging session as a Markov Decision Process and deriving the optimal policy. The optimal policy is derived using the Reinforcement Learning algorithm dynamic programming from a reward function taking electricity price and battery degradation into account. Other policies were implemented as baseline charging algorithms used for comparison, with the regular policy charging the battery as fast as possible.

The research question to be answered in this thesis was whether an intelligent charging algorithm could add value to the use of electric vehicles, and it can be concluded that it has potential to do just this by reducing the costs associated to charging.

The intelligent charging algorithm could be seen in simulations to consistently bring charging costs down compared to other baseline charging algorithms. On average, over multiple scenarios with different electricity prices and different battery costs the intelligent charging algorithm could reduce costs of at least approximately 30%. The largest savings in absolute values occurred on scenarios where: 1) the battery was expensive, 2) the charger was powerful and 3) the charging session duration was long. On these occasions the difference in costs between a regular charging session and an intelligent one could be as much as 500 SEK.

It could be observed that utilising Vehicle-to-Grid capabilities could have large effects on the difference of costs in percentage between the intelligent and regular charging algorithm. However, Vehicle-to-Grid was only used to lower costs in the case of inexpensive battery units, making the gains in absolute values smaller. Vehicle-to-Grid was not used in the intelligent charging algorithm, and could hence not be considered to contribute to lowering the charging costs, on battery units costing more than 500 000 SEK, or 1 500 SEK/kWh. Vehicle-to-Grid was not used when the differences in electricity price throughout the charging session was small. This was seen to be due to Vehicle-to-Grid needing to compensate increased costs of battery degradation by decreasing the costs of electricity from buying when prices are low and selling when prices are high.

The transition to electric transport, especially for commercial vehicles, opens up many new challenges and opportunities. It can be concluded that an intelligent charging algorithm will help in performing this transition by lowering the costs of operation.

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TRITA -EECS-EX-2020:457