Manuel Pérez Bravo

Agent-based modelling of EV charging scheduling towards optimized operation in Smart Grids

Master's thesis in Electric Power Engineering and Smart Grids
(TET4900)
Supervisor: Olav Bjarte Fosso
Co-supervisor: Salman Zaferanlouei
July 2020

Master's thesis

NTNU
Norwegian University of Science and Technology
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Preface

This Master's thesis is the conclusion to my exchange program at the Norwegian University of Science and Technology (NTNU), and also to the International Double Degree in Engineering I am finishing between the University of Seville (Spain) and the École Centrale de Lyon (France). The thesis adresses the optimization of EV charging operation within the smart grid, by means of an agent-based model and the implementation of a dynamic local pricing scheme in the stations.

I would like to thank my supervisor Olav Bjarte Fosso for his great guidance and for the trust he placed in me when I had just arrived at NTNU. His extensive experience and very valuable insight lead me to work on this topic, from which I have learnt plenty. I would also like to express my deep gratitude to my co-supervisor Salman Zaferanlouei for taking the time to guide me through all the technical matters of this topic, providing me with literature and data. I am very thankful for your very fast responses and your sincere tips for my future professional career.

During my time at NTNU, I have also been driven to this topic by the enthusiasm the professors have transmitted in their courses. I am using this opportunity to thank professors Eirin Ryeng and Denis M. Becker for conveying your interest in transportation and operational research to us. It has been an honour to be part of this university during the year 2019-2020, for how much I have grown both professionally and personally. I have felt very welcome and have learnt every single day of my stay in Norway.

Finally, I would like to extend my sincere gratitude towards my family and friends, for their unconditional support and always making me feel accompanied despite the distance.

Trondheim, July 2020

Manuel Pérez Bravo

Abstract

Transport and energy sectors are source to the majority of greenhouse gas emissions in Europe. Electric vehicles are regarded as an effective alternative towards the optimisation of the transport energy efficiency, the introduction of low-emission energies, and the shift to zero-emission vehicles. Simultaneously, there is the need of accelerating the uptake of renewable energies, with a special focus on the electricity generation. Electric vehicles can indeed also contribute to their introduction, by making the demand more flexible and adding energy storage to the system, thus tackling the variability of some renewable sources such as wind or solar.

Nevertheless, the growing adoption of electric vehicles is not only an opportunity but also a challenge. A larger fleet of vehicles, together with the tendency of increasing their battery capacity and charging rates, compromises the safe operation of the distribution grid and limits its hosting capacity. With the purpose of avoiding the physical upgrade of the network, the concept of Smart Charging arises, aligned with the principles of the Smart Grid: integrating the behavior of all users to assure the economically efficient and sustainable operation of the power grid. Among the Smart Charging set of techniques, Smart Pricing seeks fostering an efficient charging behavior by means of sending the consumers economic signals that reflect the actual cost of energy. Locational Marginal Pricing (LMP) is a market design, already in use, that enables the wholesale electric energy prices to reflect the actual cost of energy in different locations, accounting not only for the system price but also for the congestion and losses costs in the network.

In this thesis, the introduction of a pricing scheme based on LMP for the charging stations is studied. The purpose is to assess its efficiency in relocating the demand in both time and space, i.e., encouraging drivers to charge during periods of higher generation thus lower prices, while distributing the load among the stations with fewer congestion and losses costs. For this purpose, a real-time cooperative simulation tool has been developed, integrating an Agent-Based Model of the drivers' behavior, and the Optimal Power Flow of the network constraints, based on a real Norwegian local network with 856 consumers.

By analysing the response of agents to the dynamic local pricing over several days, and in comparison with two other reference scenarios, results show how the charging operation can be optimized in the short and long terms, by relocating the demand in space and time respectively. Comparing the proposed pricing scheme with the current situation in Norway, the cost of charging energy sees a reduction of up to 35% for the grid and 18% for the drivers while increasing the profit margins to the infrastructure provider, hence making the charging of electric vehicles more advantageous for all the parties involved.

Sammendrag

Transport- og energisektorer er kilde til de fleste klimagassutslippene i Europa. Elektriske kjøretøy blir sett på som et effektivt alternativ mot optimalisering av transportenergieffektivitet, innføring av lavutslippsenergier og overgangen til nullutslippskjøretøyer. Samtidig er det behovet for å akselerere opptaket av fornybare energier, med et spesielt fokus på strømproduksjonen. Elektriske kjøretøyer kan faktisk også bidra til introduksjonen deres, ved å gjøre etterspørselen mer fleksibel og legge til energilagring til systemet, og dermed takle variasjonen i noen fornybare kilder som vind eller sol.

Likevel er den økende bruken av elektriske kjøretøy ikke bare en mulighet, men også en utfordring. En større bilpark sammen med tendensen til å øke batterikapasiteten og ladeprisen, kompromitterer sikker drift av distribusjonsnettet og begrenser det. Med det formål å unngå den fysiske oppgraderingen av nettverket oppstår konseptet Smart lading, i samsvar med prinsippene i Smart Grid: integrere oppførselen til alle brukere for å sikre økonomisk effektiv og bærekraftig drift av strømnettet. Blant Smart Charging-settet med teknikker søker Smart Pricing å fremme en effektiv ladeadferd ved å sende forbrukerne økonomiske signaler som gjenspeiler de faktiske energikostnadene. Locational Marginal Pricing (LMP) er en markedsdesign som allerede er i bruk, og som gjør det mulig for grossistprisene for elektrisk energi å reflektere de faktiske energikostnadene på forskjellige steder, og ikke bare utgjør systemprisen, men også for belastning og tapskostnader i Nettverk.

I denne oppgaven studeres innføringen av et prisopplegg basert på LMP for ladestasjonene. Hensikten er å vurdere effektiviteten i å flytte etterspørselen i både tid og rom, dvs. oppfordre sjåfører til å lade i perioder med høyere generasjon og dermed lavere priser, samtidig som belastningen fordeles mellom stasjonene med færre belastninger og tapskostnader. For dette formålet er det utviklet et sanntids samarbeidende simuleringsverktøy, som integrerer en Agentbasert modell av sjåførenes oppførsel, og den optimale kraftstrømmen til nettverkets begrensninger, basert på et reelt norsk lokalt nettverk med 856 forbrukere.

Ved å analysere agensenes respons på den dynamiske lokale prisingen over flere dager, og i sammenligning med to andre referansescenarier, viser resultatene hvordan ladeaksjonen kan optimaliseres på kort og lang sikt ved å flytte etterspørselen i henholdsvis rom og tid. Sammenlignet den foreslåtte prisordningen med dagens situasjon i Norge, ser kostnadene for lading av energi en reduksjon på opptil 35 % for nettet og 18 % for sjåførene, mens de øker gevinstmarginene til infrastrukturleverandøren, og dermed gjør ladingen av elektriske kjøretøyer som er mer fordelaktig for alle involverte parter.

Acronyms

ABM Agent-based model. 4, 28, 30–32

AC Alternating Current. 14, 36, 47

BEV Battery Electric Vehicle. xiv, xviii, 8, 12, 13, 18

CCU Central Control Unit. 66–69

DC Direct Current. 13, 14, 47

DES Discrete Event Simulation. 30

EV Electric Vehicle. x, xi, xiv, xviii, xix, 1–4, 8–10, 13–19, 21, 22, 26, 28–31, 34, 46, 47, 49, 51, 52, 54, 56, 58–60, 66, 79, 81, 82, 93, 96, 98–100, 104, 105

FCE Fuel Cell Electric Vehicles. 12

GHG Greenhouse Gas. xiv, 1, 6, 15

GIS Geographic Information System. 38, 41, 47

LMP Locational Marginal Pricing. iii, v, xvi, xviii, 3, 4, 26, 28, 29, 34, 73, 78, 104, 105

OOP Object Oriented Programming. 31

OPF Optimal Power Flow. 24, 25, 28, 29, 36, 37, 42

PCR Price Coupling of Regions. 25

PEX Cross-lined Polyethylene. 46

PHEV Plug-in Electric Vehicle. 12

PVC Polyvinyl chloride. 46

REEV Range-extended Electric Vehicle. 12

SD System Dynamics. 30

SOC State of Charge. xv, xvi, 19, 32, 50, 55–57, 61, 62, 64, 65, 67, 70, 79, 80, 83, 84, 101, 102, 104

TOU Time of Use. 4, 21, 28

UN United Nations. 6, 7

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1 | Introduction

1.1 Centrality of the topic

Climate change is one of nowadays greatest challenges faced by humanity, affecting every part of the world, disrupting economy and endangering lives. It is specifically and largely addressed in both the 2030 Agenda for Sustainable Development (UN [2015]) and the 2050 European long-run strategy (European Comission), through specific goals and milestones to achieve such as the reduction of greenhouse gas emissions, the introduction of a higher share of renewables, a higher energy efficiency or the adaption of government systems.

Transport and energy sectors are inevitably targeted through these milestones, as they account for the majority of the greenhouse gas emissions. According to IRENA, around two thirds of the total Greenhouse Gas emissions originate in the energy sector, and transport accounts for a great part of the proportion left. To achieve a more sustainable scenario, the uptake of renewables has to accelerate, leaving fossil fuels behind and absorbing the majority of the electricity generation. Together with the energy transition, transport has to reduce emissions by increasing its efficiency, deploying low-emission alternative energies, and moving towards zero-emission vehicles. Electric mobility weighs positively on all these lines of action, and it has been therefore put in the spotlight of measures.

Over 90% of the total used energy in transport comes from fossil (Eurostat [2019]). In passenger transport, passenger cars have a share above 80% in inland transport in Europe, and they are mostly powered by petrol and diesel. The electrification of passenger cars in Europe is only 2.6% in average, but as high as 10.7% in countries like Norway (EAFO [2020]). Therefore, a long way is still ahead towards the climate-neutral scenario of an efficient transport sector. Most studies focusing on the evolution of the adoption of EVs, agree on the strong influence of policies and the deployment of modern infrastructure to achieve higher shares that can contribute to the decarbonisation of the sector, and the mitigation of climate change. With the purpose of elaborating efficient measures and boosting the needed infrastructure, future scenarios have to be simulated and analysed in terms of the impact they have on the other sectors.

Electric mobility has been largely discussed as a great ally to the introduction of renewables, as it introduces flexibility in the demand to absorb the variability of renewables, and it can also serve as storage to the surplus of energy introduced in the system. Thus, both sectors have to be modeled together and analyse their interdependence for future sustainable scenarios.

1.2 Motivation

The interdependence of the energy and transport sectors offers great opportunities towards decarbonisation and a climate-neutral future, however, it entails a number of challenges too. An exponential growth of the electrification of passenger transport, as the one taking place in Europe, requires the preparedness of the electrical supply grid. The energy mix can improve towards a higher share of renewables, and so can the electricity sector, but the power supply grid has to have the capacity to absorb this increase if we want the clean energy to reach its consumers.

Passenger electric vehicles are not only growing in number, but they also tend to have larger batteries and faster charging rates. Altogether, the power demand of theElectric Vehiclefleet is growing rapidly. Several studies have been performed to estimate the EV hosting capacity of the current grids in our cities, and they vary from 50% to 20% when the charging power increases (Lillebo et al. [2019], Johansson et al. [2019], Richardson et al. [2010]). Overloads in the transformers and cables seem to be the main bottleneck to this increasing penetration, and two fundamental solutions emerge: physically upgrading the grid, or optimizing the operation within, by means of implementing the Smart grid.

Upgrading the grid is significantly more expensive and comprehensive than incorporating the technology needed for the smart operation of the grid. The charging of EVs is a part of it, and then the concept of Smart Charging becomes central. Smart Charging is the set of techniques that intend to adapt the EV charging patterns towards the optimization of their energy consumption, and they can be very varied. Among them, smart pricing is one of most commonly used, meaning the sending of economic signals to drivers with the purpose of fostering a more efficient behavior.

With the introduction of renewables in the power market, market design has to evolve too, and a number of approaches are brought to the table (IRENA [2019a]). Within them, we can find the increase in the space and time granularity of the electricity markets, i.e., the more variable and accurate pricing mechanisms that reflect the actual cost of energy. A market design already in use in some parts of the world, and currently gaining importance, is the nodal pricing or Locational Marginal Pricing scheme, where energy is priced upon its actual cost at every node of the grid. Combining a more granular market design such as LMP with the smart pricing of electric vehicles can have a very positive impact on both sectors, and this is the topic of study in this thesis.

1.3 Research approach

For the purpose of studying the feasibility and opportunities of LMP market schemes in the smart pricing of EVs, a simulation tool has been developed. This simulation tool incorporates the behavioral dynamics of agents (drivers) and their charging preferences, as well as the dynamics of the electric grid in use. Both models have been put in real-time cooperation to analyse their interdependence and responsiveness. The agents' behavior has been coded in JAVA for the fitness of this language for object-oriented programming. The grid has been formulated as an Optimal Power Flow optimization problem (OPF), where we consider the minimization of costs as the objective, and all network constraints are present. This model of the grid has been solved with the MATPOWER package developed by Ray D. Zimmerman in Matlab ®.

By means of this tool, we have compared already existing charging strategies with the one hereby proposed, the Locational Marginal Pricing of energy at the charging stations. Given that the energy is charged to consumers with a profit margin for the infrastructure provider, we have also designed a pricing scheme based on LMP that relates the system cost of energy and the selling price. This pricing scheme is key to the optimization of the operation, and we it has been designed following two principles:

- Increase the market space granularity, potentiating the differences between nodal costs of energy.
- Increase the market time granularity, by reflecting energy generation fluctuations on the price.

The goal of this pricing scheme is to relocate and optimize charging operation in both time and space, so that drivers adapt to the introduction of renewables, and the social cost of charging decreases.

1.4 Contribution

This thesis has further developed a simulation tool for real-time coordination of the responses by the two main components of the system, the agents and the electric grid. Smart pricing strategies can be compared by means of this tool, and both the opportunities and challenges of adopting novel market LMP schemes are studied:

- A simulation tool has been developed, where the agents are modeled individually by means of an Agent-based model which brings responsivess to the pricing strategies and sheds light on emerging phenomena. This simulation tool is a combination of JAVA object-oriented programming, and the electrical model of the grid in MATPOWER (Matlab® package).

- Different smart charging strategies have been compared in terms of the cost of energy they entail, using the aforementioned simulation tool.

- This study considers energy generation fluctuations over the same day and along several days, to illustrate the variability of renewable energies in the system, and the opportunities of relocating the demand over time. The system price is given hour by hour, unlike most Time of Use schemes who divide the day into a few intervals.

- A pricing scheme has been proposed based on LMP for the charging energy at the stations, and its effect on the agents' behavior has been studied, as well as the consequences on the overall cost of charging energy for the fleet of EVs.

- This thesis focuses on the use of fast charging stations in public facilities. There is scarce literature in modeling the charging behavior of agents among fast public stations, however, their presence and use are markedly growing due to the faster charging rates and larger batteries of nowadays EVs that allow agents to charge without much previous thought.

1.5 Thesis outline

The thesis is structured in six chapters, as well as a preface, abstract and one appendix.

First, an introduction of the thesis is given, describing briefly the motivation of this topic, a summary of the research approach, and the intended contribution of this work. Then, a second chapter describes the background of this topic, from the evolution of the electric vehicles in Norway, to the opportunities and challenges their adoption implies for the grid. Theoretical concepts about electrical grid and behavior models are also presented in this chapter. The third and forth chapter describe the methodology followed to study the impact of different smart charging strategies on the cost of energy. The model chapter describes in detail all assumptions and methods used to model the dynamics of the system, and chapter four summarizes the simulation scenarios and their implications. Chapter five gives an overview of the results obtained for all the simulations previously defined, and establishes discussion by comparison. Finally, the sixth chapter outlines the main conclusions of this work, and proposes some guidelines for future research that extends the topic hereby treated.

2 | Background

2.1 The evolution of the Electrical Vehicle: The case of Norway.

Transport plays a pivotal role in the sustainable development of societies and it is indeed directly and indirectly targeted through all 17 UN's sustainable development goals, as it is both in the problem and the solution (United Nations [2019]). For instance, transport can make human settlements more inclusive and resilient, however, it is very energy and material demanding, and it has a large impact on emissions, land use and human health.

In Europe, transport represents almost a quarter of the greenhouse gas emissions and it is the main cause of air pollution in cities (European Comission [2016]). Unlike other sectors, transport has not seen a gradual decline in emissions (see figure 2.1) .

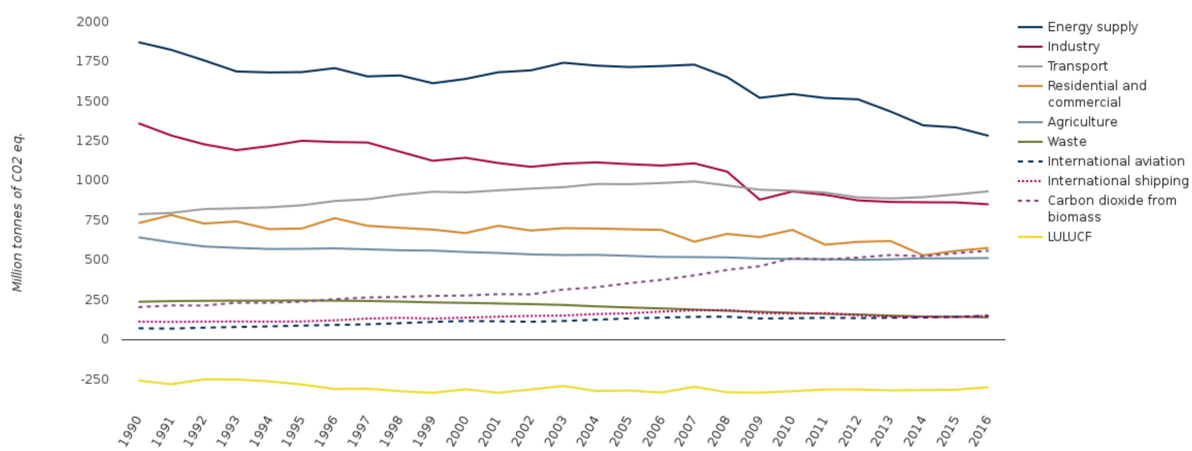


Figure 2.1: GHG Emissions by sector in the EU-28, 1990-2016 (Source: EEA).

Within the 2030 Agenda for Sustainable Development developed in 2015, the need of tackling climate change is largely addressed (UN Sustanability Goal 13, UN [2015]), and countries adopted the Paris Agreement (2015) to limit global temperature rise to well below 2 degrees Celsius. This is the first-ever universal and legally binding global climate change agreement. Within this agreement, the first key element to be approached, is the mitigation through the reduction of emissions (UNFCCC). Transport is therefore very specifically targeted in this long-term climate neutrality goal, and since the signature of the agreement, countries are expected to submit an updated National Determined Contributions report (NDC) every five years. This report includes, among others, their commitment and progression in the reduction of transport-related CO_2.

Following the agreement, the Norwegian government made the commitment to link Norwegian climate change policy to that of the European Union, and the National Transport plan towards 2029 outlines a very ambitious strategy in the transport sector, with emissions reduced by 50% before 2030 (Fridstrom et al.). Three main lines of action can be highlighted from this joint European coordination towards low-emission mobility (European Comission [2016]):

- Optimising the transport system and improving its efficiency.
- Scaling up the use of low-emission alternative energy for transport.
- Moving towards zero-emission vehicles.

Electric vehicles are proposed as a very plausible (although partial) solution to each of the aforementioned lines of action. The reason is that electric vehicles can substantially reduce emissions in urban areas, while minimizing consumption by improving their energetic efficiency and fostering the inclusion of new transport modes. Nevertheless, the complete life cycle of the vehicles has to be studied in order to assess their net impact on the environment. For instance, the materials used for the manufacturing of batteries, or the energy mix from which the power is supplied can neutralize their positive impact. Therefore, a coordinated plan with the energy sector is to be implemented.

According to the International Energy Agency (IEA [2020]), this life cycle assessment of electric vehicles has a net positive impact on the reduction of emissions (see figure 2.2), in mid-size cars with a battery capacity of 40 and 80 kWh.

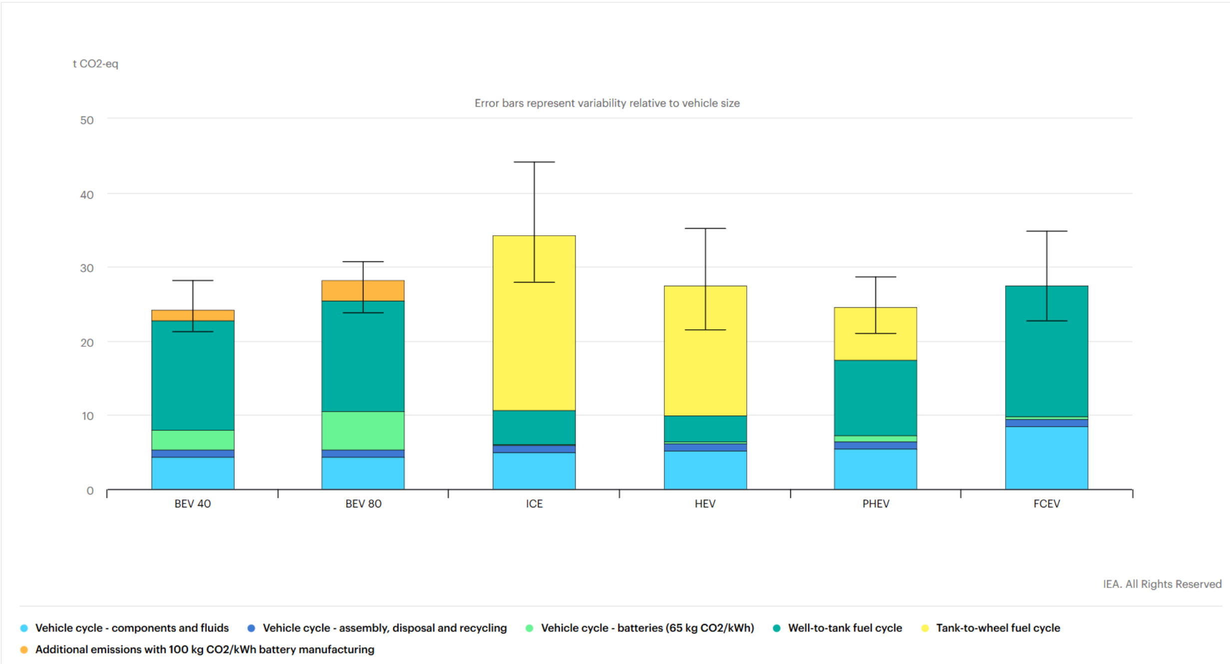


Figure 2.2: Comparative life-cycle greenhouse gas emissions over ten year lifetime of an average mid-size car by powertrain, 2018. Source: Global EV Outlook 2020 (IEA [2020])

The market penetration of EVs is still at an early stage where countries show very distant scenarios, but the increase in the global stock of EVs is exponentially growing (IEA [2020]). The highest shares of EVs in the world are present in China (4.9%), followed by Europe (3.5%) and the United States (2.1%). Still, large differences can be seen among European countries (see figure 2.4 and American states.

Globally, the leading country in EV adoption is Norway, with the highest share of 10.7% in 2020. At the core of this phenomenon is the Norwegian climate policy that has made BEVs economically accesible and attractive to drivers (Figenbaum et al. [2015]). Originally, the incentives were introduced to help the market of BEVs take off, at a time when they were expensive and barely present. Nowadays, the renovated Norwegian fleet is on the track to reach the level needed to support the 85 g CO_2/km target. Indeed, it has been largely discussed in international studies that the penetration and therefore the effect of EVs in the mitigation of climate change, is strongly determined by the policies implemented (Tsakalidis and Thiel [2018]).

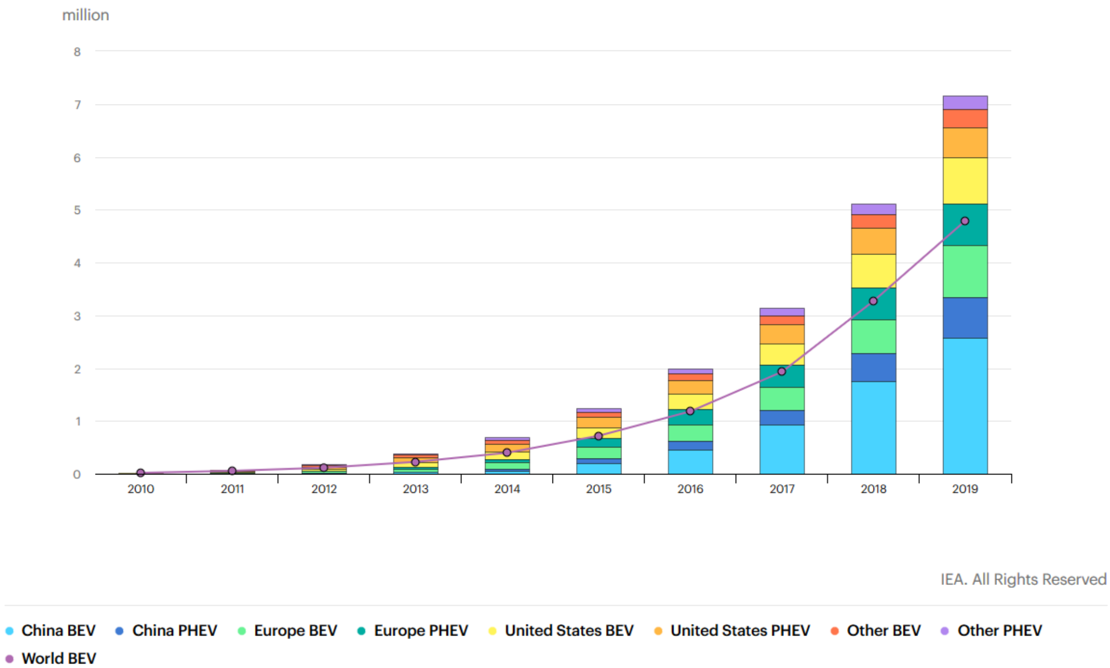


Figure 2.3: Global electric car stock, 2010- 2019. Source: Global EV Outlook 2020, IEA [2020]

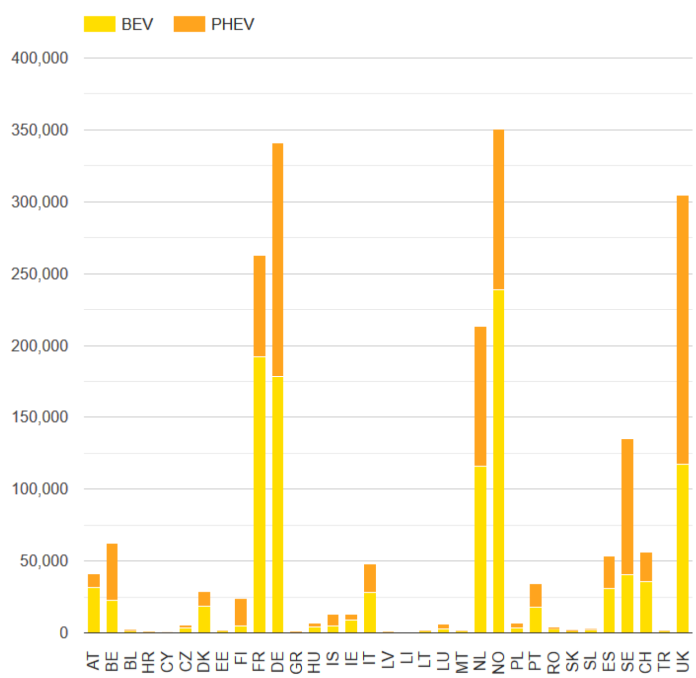


Figure 2.4: Countries overview in the number of electric vehicles in Europe. Source: European Alternative Fuels Observatory (EAFO [2020]).

The adoption of electric vehicles can also encounter a second bottleneck in the infrastructure. Tendencies show how the charging power has increased in the last years from slow charging to a majority of vehicles with fast charging rates (over 22 kW) (EAFO [2020]), accompanied by an increase in the number of fast charging stations in the country (see figure

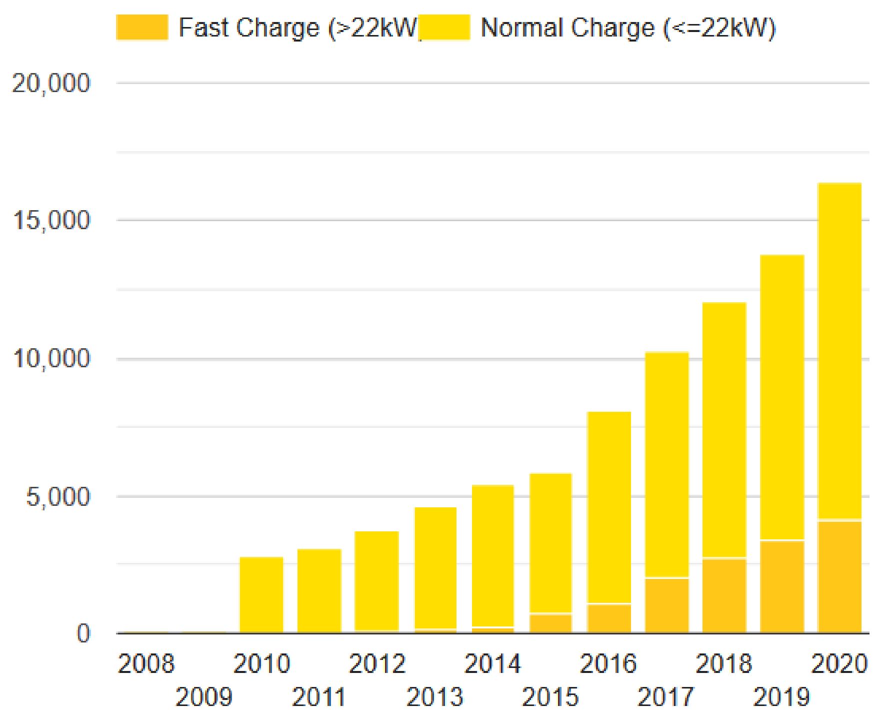
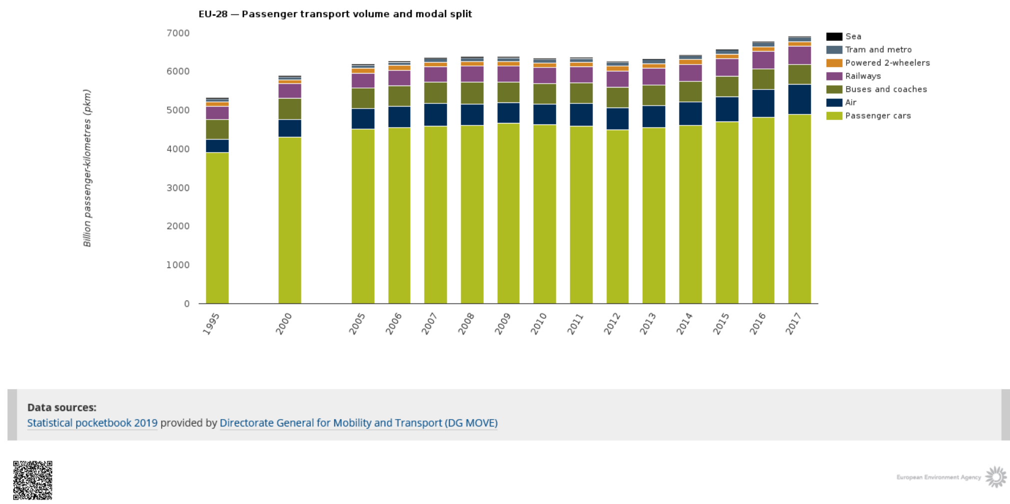
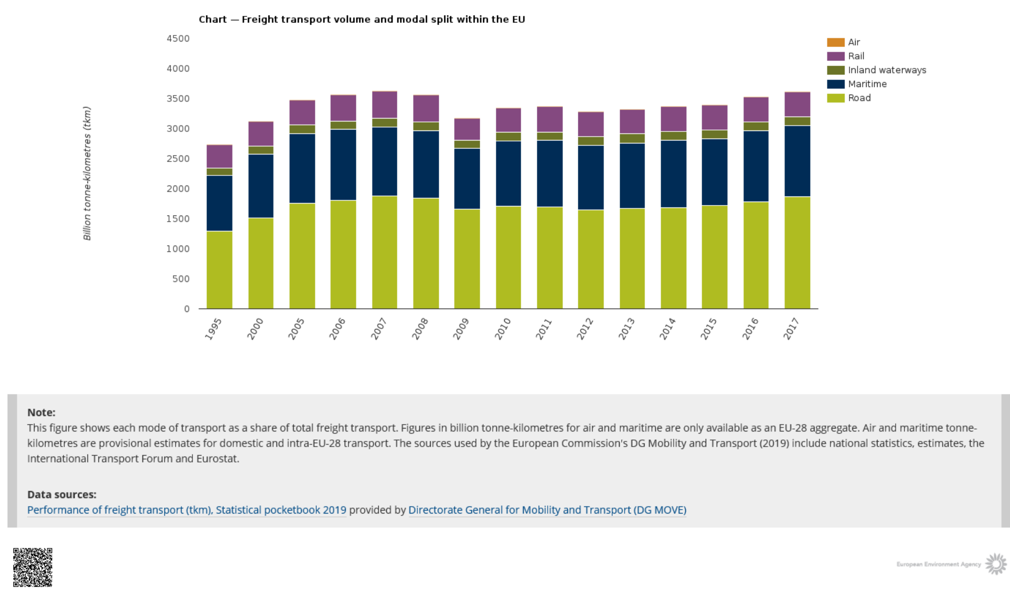


Figure 2.5: Evolution of normal and fast charging public points in Norway. Source: European Alternative Fuels Observatory (EAFO [2020])

Road transport has a significantly higher share than the other modes in Europe, both in passenger and freight transport (see figure 2.6). Therefore, changing the paradigm of the power trains of road transport vehicles, implies a large structural shift across the energy consumption of the transport sector. Many have already pointed out the potential but also challenges that the large adoption of passenger EVs might imply for the electrical grid of supply. This is what motivates the smart charging operation of vehicles in the grid, which will be discussed in section 2.3.



(a) Volume of passenger transport in Europe and modal split.



(b) Volume of freight transport in Europe and modal split.

Figure 2.6: Charts of passenger and freight transport volumes in Europe. Source: DG-MOVE and Transport [2019]

2.2 Electric vehicles and charging stations. Classification and standards.

Electric vehicles refer to the electrification of the automotive powertrain, and for which the electric motor is the primary source of propulsion (Amsterdam Roundtable Foundation and McKinsey & Company The

Netherlands [2014]). Under this definition, we can distinguish Plug-in Electric Vehicle, Range-extended Electric Vehicle, Battery Electric Vehicle and Fuel Cell Electric Vehicles. Sometimes, conventional hybrid electric vehicles (HEVs) are also included under the umbrella of electric vehicles, but in this type the electric motor is not the primary source of propulsion but a complementary one. The main differences between them can be appreciated in figure 2.7.

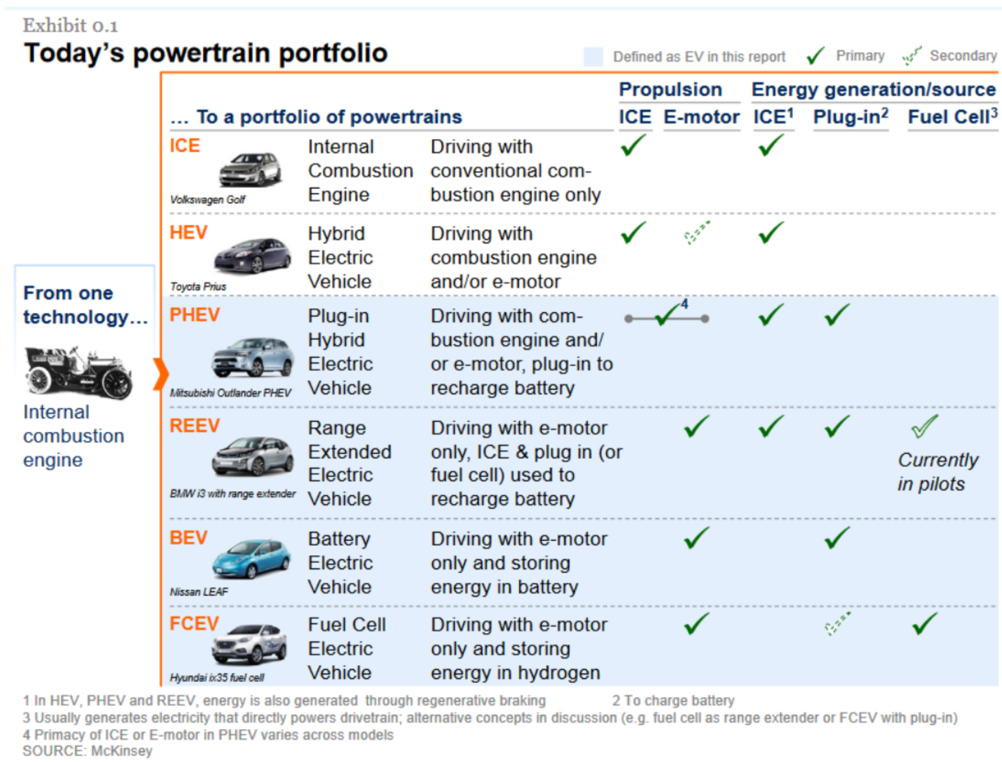


Figure 2.7: Types of electric vehicles. Source: Amsterdam Roundtable Foundation and McKinsey & Company The Netherlands [2014]

Among these types of EV, the most common are the PHEVs and BEVs. In Europe, BEV predominates over the PHEVs, and in Norway, the difference is even more notorious. In 2020, the number of new registered cars in Europe (in % relative to the total newly registered cars) was 4.1% and 3.3% for BEVs and PHEVs respectively (EAFO [2020]). In Norway, the number of new BEVs more than duplicates the number of PHEVs (48.9% to 20.6%). For that reason, this study will focus in the charging operation of only BEVs.

BEVs are mostly mid-size passenger cars, but they present quite a large range of characteristics among models. In Norway, for quite some time, the most common models were Nissan Leaf (27.8%), Volkswagen e-Golf (16%) and Tesla Model S (11.6%), according to the report ellaborated by the Zero Emission Neighbourhoods in Smart Cities Center in 2018 (Sørensen et al. [2018]). Nowadays, trends have slightly shifted and new models have taken a higher position in the rank, such as the BMW i3 (10.3% of BEVs in 2020), however, the same three most common models maintain a top position in the Norwegian fleet with shares of 17.8%, 17% and 8.5% respectively (EAFO [2020]).

In this study, three models will be used for simulation, and they are: Nissan Leaf, Volkswagen e-Golf and Tesla Model S. The reason of holding on to the previous rank of models is the previous work that has been developed around them. Previous master thesis and journal articles have been published by this department in the simulation and integration of these vehicles in the electrical grid (Eilertsen [2013],Harbo et al. [2018]). Nevertheless, the features of these vehicles have been upgraded over time, and these updates are considered in the thesis, summarized in the table 2.1.

Table 2.1: Most common BEV models in Norway. Source: European Altenative Fuels Observatory (EAFO [2020])

EV model	Number (% BEVs) in Norway	Net battery capacity (kWh)	Approx. range in Norway (km)	Fast charging (kW DC)
Nissan Leaf (Nissan-Norge [2019]	17.8%	40.0	240	50, ChaDeMo
Volkswagen e-Golf (Volkswagen-Norge [2018]	17	35.8	215	40, CCS
Tesla Model S (Tesla-Norge)	8.5 %	150.0	505	Supercharger, 150

The trend among EVs is to augment the battery capacity and the charging rate. Among Norwegian drivers, the main concern about BEVs is the battery range, since in a sparsely populated country, driving distances are longer in average (Figenbaum et al. [2015]). With a higher battery capacity and charging rate, driving a BEV becomes similar to driving an ICE, with which the range anxiety was lower, given the number of petrol stations and the sufficient range of the tank.

With the emergence of increasingly fast charging stations, the classification of charging modes is made by means of the configuration of the charging point. The most used standard for charging points is the one defined by the International Electrotechnical Comission in the first part of their IEC 61851 standard. Under this standard, we can identify four charging modes defined as follows:

- Mode 1: Domestic socket and extension cord

  The vehicle is connected to the grid by means of a standard socket-outlet of an AC supply, using a cable a plug. The rated values for the current and voltage under this mode must not exceed 16 A and 250 / 480 V AC in single-phase / three-phase respectively.

- Mode 2: Dmestic socket and extension, incluiding a protective device

  The vehicle is, as before, connected to a standard socket-outlet of an AC supply, but incluiding a control pilot function and system for personal protecion against electric shock between the standard plug and the EV. The rated values for current and voltage under this mode must not exceed 32 A and 250 / 480 V AC in single-phase / three-phase respectively.

- Mode 3: Socket in a dedicated circuit

  The connection goes from the EV to an AC EV supply equipment that is permanently connected to an AC supply network, incluiding a control pilot function from the AC EV supply equipment to the EV.

- Mode 4: Direct current fast charging

  The connection of an EV to an AC or DC network utilizing a DC EV supply equipment, incluiding a control pilot function from the DC EV supply equipment to the EV.

  The key to fast charging stations is indeed the off-board fast charging module, allowing higher rates (Folkson [2014]) and all fast charging station above 22 kW, therefore all considered stations in this study are defined by this fourth mode.

Worldwide, the country with the highest number of fast-charging stations is China, where 82% of the accessible fast-charging points are located (IEA [2020]), followed by the United Stated, Japan and Norway. This number of fast-charging points has been increasing rapidly at a higher rate than the so-called normal chargers, attaining the number of 4080 in 2020 in Norway (EAFO [2020]).

In Norway, the majority of the fast charging stations are operated by Fortum Charge & Drive, Grønn Kontakt, BKK/Lyse and Tesla Superchargers. All of them, except for Tesla, charge per both time and the power consummed. Their presence and pricing schemes are summoned in table 2.2.

Table 2.2: Main fast-charging stations providers in Norway. Source : elbil.no

Provider	Number of fast-charging stations in Norway	Price (Fast-charging)
Fortum Charge & Drive	310	$2\frac{kr}{min}+2.5\frac{kr}{kWh}$
Grønn Kontakt	240	$1.25\frac{kr}{min}+2.9\frac{kr}{kWh}$
BKK/Lyse	80	$1.25\frac{kr}{min}+2.9\frac{kr}{kWh}$
Tesla Supercharger	60	$1.7\frac{kr}{kWh}$

2.3 Opportunities and challenges of integrating EVs in the smart grid.

Electric mobility shows numerous advantages in terms of impact for the transport sector transition, as we have described before. The even more relevant sector to consider towards achieving the long-term goal of climate neutrality is the energetic sector. Around two-thirds of GHG emission are originated from energy production and use, and the remaining 35% is distributed among transport, building and district heating, according to IRENA [2017]. As of today, 84% of the energy comes from fossil fuels and only 16% from renewable sources. In order to reach the goals established in the Paris Agreement (UNFCCC), countries would have to accelerate the uptake and base 65% of their energetic consumption on renewables by 2050. This target is presented as a feasible milestone in the energy roadmap defined by IRENA. The use of renewable energies in the electricity generation would consequently see an increase from today's 25% to 80%.

In the numerous analysis studying the interdependence of the transport and energy sectors, electric mobility is mentioned in both the challenges and the solutions. At a glance, electric mobility can contribute in making the demand more flexible and efficient, but it is also an increased load for the electrical grid. In this subsection, we will present the double-edged effects of introducing electric mobility in the smart grid.

2.3.1 The Smart Grid

A Smart Grid can be defined as an electricity network able to efficiently integrate the behavior and actions of all users connected to it (generators, consumers, and those who play both roles) with the purpose of ensuring economically efficient, sustainable power system with low losses and high levels of quality and security of the supply (European Comission [2012]). In relation to the integration of renewable energies here at issue, the smart grid can accommodate the following characteristics needed (IRENA [2013]):

- *Variability*: In particular, solar and wind energies are dependent on every-varying natural resources. Given that the electricity demand must be at all times supplied, the smart grid has the role of allocating or storing the generated power.

- *Distributed generation*: When generation systems become smaller and distributed in the grid, the new business model shall allow those system to connect to the grid. Special attention must be paid to the safety and stability of their operation within.

- *High initial cost*: Renewable energies are often very expensive to install, even if their operation costs are lower and they are more cost-effective on a lifecycle basis. Smart Grids can address the capital requirements through enhancing private investment in electricity systems by allowing distributed generation.

2.3.2 Introducing demand flexibility: The EV as a solution

There is great leverage in absorbing the variability of renewable energies by means of the demand flexibility of EVs. Knezović [2017] defines the flexibility of EV power demand in terms of (1) the direction (G2V/V2G), (2) the power capacity, (3) the starting time, (4) and the duration.

In the landscape of innovations for a renewable-powered future developed by IRENA [2019a], we find the smart charging of electric vehicles within the main enabling technologies (see figure 2.8). Electric vehicles do not only introduce demand-side flexibility, they also add decentralized storage in the system. On the demand side, smart charging of EVs can adapt the charging cycle to the generation events in the power systems with a balancing effect. This can help mitigate the curtailment of renewables and avoid extra load during peak times. On the storage side, V2G technologies can even bring a greater flexibility by supplying power from the batteries of cars to the system when needed.

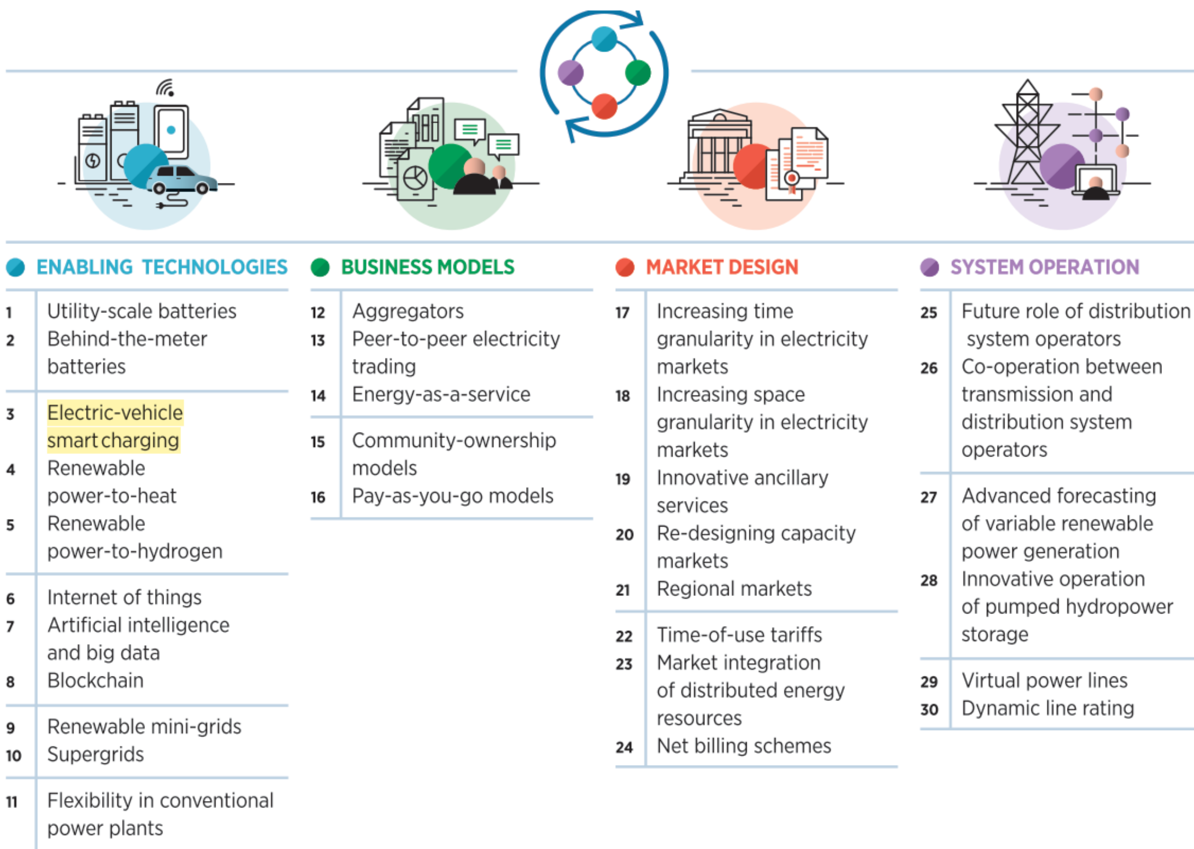


Figure 2.8: The landscape of innovations for a renewable-powered future. Source: IRENA [2019a]

2.3.3 Increasing the power demand: The challege of hosting EVs

Many are the analyses focused on the future hosting capacity of EVs in the current distribution grids. The exponential growth of EVs in Europe (and more remarkably in Norway), has raised concerns on the grid hosting capacity before reaching the limits of safe operation. In the Energy Insights report developed by Engel et al. [2018], they estimate a 40 TWh power demand increase owing to the road transport electrification in Germany alone (see figure 2.9).

In the Norwegian context, we have the results of Lillebo et al. [2019] exploring the effects of increasing EV penetration levels on the distribution grid. In a fast-charging scenario, the findings estimate that the grid can tolerate up to 50% EV penetration regarding voltage deviation, and 20% with regard to the rated power of the weakest cable. Very similar results have been obtained for other countries: Johansson et al. [2019] calculates the EV hosting capacity of the Swedish distribution network between 50 and 25% when the charging power increases. In Dublin (Ireland), Richardson et al. [2010] have also estimated the maximum penetration between 20 and 40%.

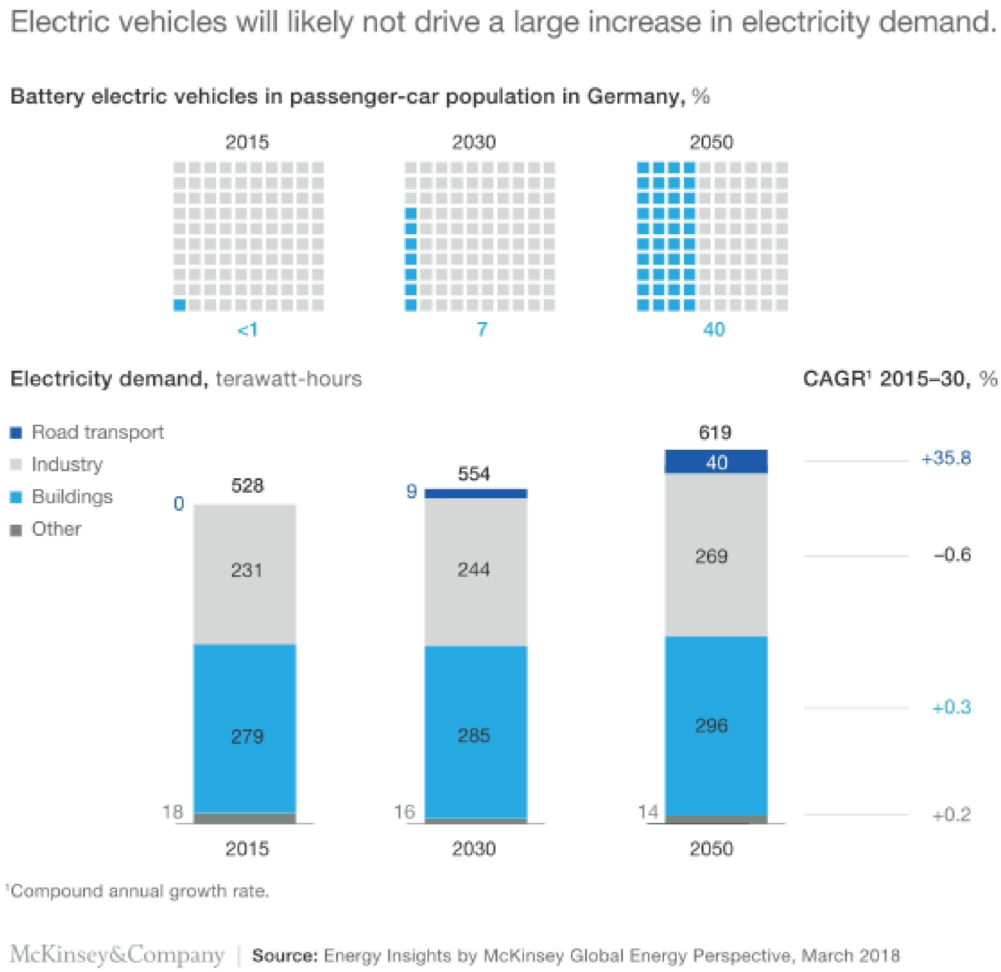


Figure 2.9: The effects of BEV adoption increase in Germany on the electricity demand. Source: Engel et al. [2018]

All aforementioned studies share the vision that the transformers and cables are the most vulnerable components, as they are the first to be overloaded. Two main strategies are proposed to work around this problem: physically upgrading the grid, or optimizing the operation. Augmenting the grid capacity is much more expensive and comprehensive than making the grid "smarter" by inserting smart meters and optimizing the opration.

All in all, a larger EV penetration in the grid can be studied through three main dimensions, on which we will later propose actuation methods to reduce the impact (Lopes et al. [2011]):

- Transmission line congestion
- Voltage drop
- Energy losses in the system

Longer discussion on how these phenomena increase the total cost of energy and how to reduce them will be analyzed in section 2.5 and 4.

2.4 Smart Charging

Aligned with the concept of the Smart Grid, Smart Charging is the solution to hosting a greater penetration of EVs in the grid without the need of physically upgrading the system. Smart Charging can be defined as the set of techniques that intend to adapt the EV battery charging patterns towards the optimization of energy consumption. It is a term seldom defined and often used, and another definition that also fits this thesis very well is the one of the company FleetCarma. They define Smart charging as the intelligent form of charging where the load is shifted based on grid status and in accordance to the drivers' needs (FleetCarma [2017]).

Among these techniques defined under the term of Smart charging, we can distinguish three main lines of action: Smart Pricing, Smart Technology and Smart Infrastructure (Hildermeier et al. [2019]). An overview of these techniques and some implementation examples are summarized in table 2.3. In turn, these techniques can be implemented in two different control architectures (García-Villalobos et al. [2014]):

- Centralized control architecture

  The aggregator is responsible for directly managing all EVs within its region. This control can be done by day-ahead profile forecast or in real time. As it is our interest in this thesis, real-time centralized management implies that the aggregator must collect data from EVs (incluiding their identification, SOCand user preferences).

  With the data of agents, the aggregator will optimize operation and organize the demand in a way that satisfies both the agents and the grid constraints. The optimization objective of the aggregator can be very diverse. For istance, the objective can be the frequency regulation, voltage regulation, the generation cost, the load levelling, etc. A full review of these techniques can be seen in García-Villalobos et al. [2014].

- Decentralized control architecture

  Also known as distributed or local control, the decisions rest on each EV owner rather than the aggregator. However, these decisions can be influenced by means of the factors upon which the agents decide, for instance, the station location or the price. The role of the aggregator in this case, is merely that of sending the appropriate (economic) signals to the agents when fostering a more efficient operation.

As for centralized control, the optimization objective of the signals can be varied, ranging from frequency regulation to the minimization of costs. Among the most commonly used formulations, we can find: convex optimization, dynamic optimization, game theory, genetic algorithms and graph search algorithms.

If we compare both control architectures, we can see that centralized control can provide a better usage of the network, since all information of demand and supply sides are known by the aggregator. On the other hand, it requires a strong communication infrastructure and the voluntary participation of drivers in the market pool. These requirements make it poorly scalable and computationally impractical.

Decentralized control is easily scalable, requires less communication infrastructure and the user does not need to share its details or delegate the decisions related to the charging behavior. However, there is a greater uncertainty in the final result, and there is still the need of forecasting the reaction of consumers to the economic signals sent by the aggregator. To overcome this challenge, several simulation environments have been developed, incluiding the one in this thesis.

For their very own definition, some smart charging strategies are better defined under a centralized or decentralized control architecture. For instance, smart pricing tends to be based on decentralized control schemes, while smart infrastructure strategies tends to be part of a centralized control.

Table 2.3: Smart Charging strategies overview

Strategy	Description	Current state, implementation examples
Smart Pricing	Consumers receive economic signals reflecting the actual cost of energy at a given time. The goal is to reward or penalize agents to foster a charging behavior beneficial to the grid, i.e., avoiding load peaks, losses and congestion.	At present, most pricing schemes in Europe apply the standard tariff, based on a flat kWh charge for the demand. This way, agents are not aware and do not act regarding the actual cost the energy. Even if pilot projects have shown large participation and impact on the operation, the current pricing models are simple delineations of binary meters. For instance, the two-period TOU in Spain (IRENA [2019c] or the Octopus Agile in UK (Octopus Energy [2018]) can help filling the night valley and reduce the day peak. Real-time pricing, on the other hand, changes by short intervals according to the grid situation. Therefore, they require smart metering, which deployment has been lagging behind in most countries.
Smart Technology	The automated operation can also optimize energy consumption by adjusting loads based on price signals, without the need of active intervention by the consumer. However, smart technology has proven to be less efficient when it is not coupled with Smart Pricing, as it does not encourage behavioral changes in agents.	This is case of many proposals that exploit the fact that EVs are often connected longer than they actually need to fully charge. Under these circumstances, a local aggregator, whether at the level of the charging station or upstream, adjusts the charging power and intervals depending on the grid status and the needs of the vehicles. Examples of these techniques are present in the residential low-voltage system optimization proposed by Alonso et al. [2014], or in the three-layer EV charging infrastructure presented in Khaki et al. [2019].

Smart Infrastructure	Research shows that holistic planning of the charging infrastructure can also increase utilization rates, avoiding unnecessary investments in underused stations and longer trips than necessary by agents.	The problem of station location is simply a new application to the well-known optimization location problem. It is a multi-objective optimization problem, and the most used formulations (Point Demand, Traffic Demand and Hybrid Model) are abstractions of real scenarios. At present, most station location algorithms are traditional adaptive ones represented by genetic algorithms. Deep Learning has taken over in the last years, introducing several benefits for its excellent performance in large-scale data sets and evolvability (Zhang et al. [2019]). Some new ideas have also emerged lately in the relaxation of the charging stations location. For instance, several companies have developed movable chargers that can operate within a parking space or across the city. Some examples of this technology are given: • Mob-Energy (France): The charging robot integrates second-life batteries, and they move across a parking lot (Mob-Energy [2020]). • Chargery (Germany): The charging modules are bike-delivered across the city (Chargery [2020]). • SparkCharge (USA): Portable and ultrafast vehicle charging units, to bring bring in the trunk in case of running out of battery on the way (Spa [2020]).

2.5 Smart Pricing: Locational Marginal Pricing

As we have seen before, the larger demand of power, generated by the growth in the EV fleet, might incur the violation of the grid constraints to operate in a stable and safe way. This impact can be quantified through the result it has on:

- Transmission line congestion

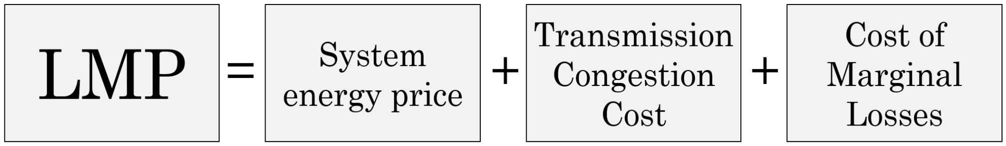


Figure 2.10: LMP components. Source: EnergyAcuity [2018]

- Voltage drop
- Energy losses in the system

If we want to send the agents signals about the actual cost of energy with the purpose of making the them adopt a more efficient charging behavior, this signal should include the cost of the aforementioned constraints. That is exactly the purpose of nodal price of energy (also called Locational Maginal Price, LMP), which can be defined as the price paid for generated or consumed electricity at a given transmission node (IRENA [2019b]). Consequently, different nodes in the same distribution system will incur in different prices of energy due to the grid configuration and state (loads, generation, losses, etc.). The components of the nodal price can be split into three components: the system energy price, the transmission congestion cost, and the cost of marginal losses (Feiyu [2004]).

First, we must determine the way the nodal price is calculated.

2.5.1 Power Systems Optimization

In power system optimization, we can mainly find three types of problems commonly referred to: power flow (load flow), economic dispatch, and optimal power flow (Cain et al. [2012]):

- In the economic dispatch problem, the goal is to meet the demand (P_D)with the cheapest generators that can supply it. If c_i is the marginal cost of energy at a given generator i, and P_{G_i} is the power generated by this generator, the economic dispatch problem can be formulated as (DTU):

$$\begin{aligned} \text{minimize} \quad & \sum_i c_i P_{G_i} \\ \text{subject to} \quad & P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max}, \\ & \sum_i P_{Gi} = P_D \end{aligned} \tag{2.1}$$

As we can see in the formulation, the economic dispatch does not consider the network flows or constraints. The network is assumed to be a copperplate, where all flows from any point A to any point B is lossless.

Indeed, the economic dispatch problem can be solved by means of the merit-order curve, where we assign demand to the cheapest (sorted) generators up to their limits and until the whole demand is satisfied.

- In the load (power) flow problem, the voltage magnitudes constraints and the losses are considered, in order to obtain complete voltage angle and magnitude information for each bus in a power system. In each bus i, the active and reactive power injections are calculated as follows (Seifi and Sepasian [2011]):

$$P_i = P_{G_i} - P_{D_i} \tag{2.2}$$

$$Q_i = Q_{G_i} - Q_{D_i} \tag{2.3}$$

  If we also apply Kirchhoff's law to each of these buses, being G_{ik}, B_{ik} the real and imaginary parts of the bus admittance matrix Y_{BUS}, and θ_{ik} the voltage angle between the i^{th} and the k^{th} buses, the power balance equations are:

$$P_i = \sum_{k=1}^{N} |Y_{ik}||V_i||V_k|(G_{ik}cos(\theta_{ik}) + B_{ik}sin(\theta_{ik})) \tag{2.4}$$

$$Q_i = \sum_{k=1}^{N} |Y_{ik}||V_i||V_k|(G_{ik}sin(\theta_{ik}) - B_{ik}cos(\theta_{ik})) \tag{2.5}$$

  The power flow problem formulation is not an optimization problem in itself, as it does not consider generation costs, and only assigns flows in the network to supply the demand, by enforcing power balance in the buses.

- The Optimal Power Flow (OPF), on the other hand, finds the objective value to an objective function, subject to the power flow and operational constraints expressed in the power flow problem (generator capacity, transmission stability, switching mechanical equipment, etc.). Most OPF formulations are based on the classical formulation of its creator (Carpentier, 1962) and Dommel and Tinney [1968]. In this classical formulation, the objective is to minimize the total cost of electricity generation while maintaining the system within safe operation conditions.

If the system is composed of **N** buses connected by means of **L** branches, with **G** controllable generators located on a subset ob buses ($G \subseteq N$). The cost of each of these generators is a function of their output power, $C_i(P_i^G)$. The mathematical formulation results as follows (Frank and Rebennack [2016]):

$$\begin{aligned}
\text{minimize} \quad & \sum_{i \in G} C_i(P_i^G) && \text{(2.6a)}\\
\text{subject to} \quad & P_i = \sum_{k=1}^{N} |Y_{ik}||V_i||V_k|(G_{ik} cos(\theta_{ik}) + B_{ik} sin(\theta_{ik})) \; \forall i \in \mathbf{N}, && \text{(2.6b)}\\
& Q_i = \sum_{k=1}^{N} |Y_{ik}||V_i||V_k|(G_{ik} sin(\theta_{ik}) - B_{ik} cos(\theta_{ik})) \; \forall i \in \mathbf{N}, && \text{(2.6c)}\\
& P_i^{G,min} \leq P_i^G \leq P_i^{G,max} \; \forall i \in \mathbf{G}, && \text{(2.6d)}\\
& Q_i^{G,min} \leq Q_i^G \leq Q_i^{G,max} \; \forall i \in \mathbf{G}, && \text{(2.6e)}\\
& V_i^{min} \leq V_i \leq V_i^{max} \; \forall i \in \mathbf{N}, && \text{(2.6f)}\\
& \theta_i^{min} \leq \theta_i \leq \theta_i^{max} \; \forall i \in \mathbf{N} && \text{(2.6g)}
\end{aligned}$$

We can identify the first two constraints as the power flow equations previously defined. Third and fourth constraints correspond to the limits of the generators, and the last two, to the voltage magnitude and angle limits to be respected in each bus.

It is clear that, to determine the actual cost of energy at every bus of a system, it is necessary to consider flows and constraints of the network. Therefore, the economic dispatch optimization of the network won't be sufficient to calculate the nodal prices, and they are only obtained by means of the OPF formulation.

The OPF, as a non-linear, non-convex problem, has thousands of variables and constraints for all buses and lines of the system. It was first proposed in France (Carpentier, 1962) for the French transport network. As of today, it is used in California (USA, CAISO) in intervals of 5 to 60 minutes, in the East Coast of the United States (PJM) in intervals of 5 minutes, and in Europe in a day-ahead basis, to calculate electricity prices across Europe. The 19 European Countries participating in this day-ahead price clearance are the cluster defined as Price Coupling of Regions, which is an initiative of eight Power Exchanges, incluiding the Nordic market NordPool.

In the formulation of OPF, nodal prices, which is the actual cost of energy at each node of the system, are calculated as the lagrangian multipliers of the equality constraints (2.6gb, 2.6gc). Therefore, if the solve the optimal power flow for the system at issue, the nodal prices will be calculated as well.

2.5.2 Locational Marginal Pricing

At a market level, based on the nodal prices calculated for each node of the system, it is possible to charge energy at a proportional price of its actual cost. This is the Locational Marginal Pricing or nodal pricing scheme. According to IRENA [2019b], market designs in Europe can be fundamentally divided into two types:

- Zonal Pricing: The nodes are grouped by pricing zones, which are the largest area within which participants can trade energy without capacity allocation, which means that congestion within the area must be low. This zones are defined by the regulator or the transmission system operator. For most of European countries, pricing zones are its national borders, others have several bidding zones within the country, like Norway (see figure 2.11).
- Nodal Pricing: All transmission constraints are considered when determining the optimal dispatch of energy in the system and deriving marginal prices for all nodes in it. This design is already used in Argentina, Chile, Ireland, New Zealand, Russia, Singapore and several US states (Holmberg and Lazarczyk [2012a]).

Going back to the innovations landscape defined by IRENA [2019a] in figure 2.8, the market design is one of the four main strategies to integrate renewable energies effectively. Under this set of strategies, we find the need for increasing both space and time granularity in the market. While nodal pricing might entail a more challenging implementation, it is deemed more efficient in reflecting the transmission constraints in the system, fostering a more efficient operation.

2.5.3 Locational Marginal Pricing in the operation of EV charging

We have mentioned before the opportunities that LMP present in fostering a more efficient operation in the system on the part of the agents, by pricing energy according to its actual cost at every node. LMP can relocate demand in terms of time and space, as agents will avoid high prices at times of demand peaks and at places where the energy cost is higher due to congestion and losses in the network.

The same principle applies to the energy demand originated in the charging of electric vehicles, and this

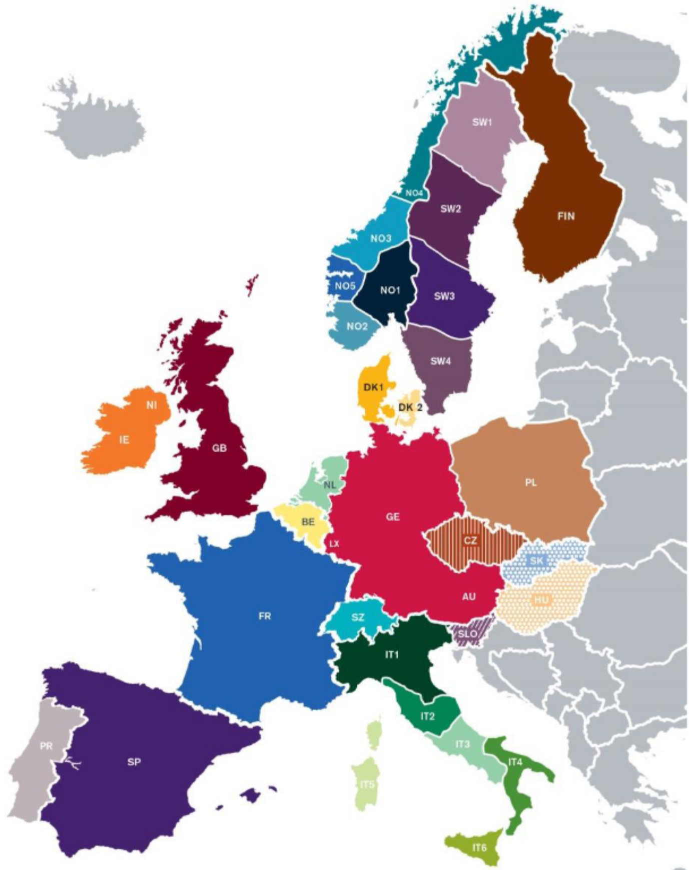


Figure 2.11: Bidding zones in Europe. Source: Ofgem [2014]

is the matter of study in this thesis. By charging the energy proportionally to its actual cost at the stations, agents are influenced towards relocating their demand when the energy is cheaper (higher generation levels) and at the cheapest stations (where the network is less congested and has the least losses). Therefore, by increasing granularity in time and space of the energy market, operation is optimized in time and space as well.

Previous work has been done on this topics, showing very promising results. The main references collected, as well as this very thesis contribution, are summarized in table 2.4.

Table 2.4: Review of the previous work done on the application of LMP smart pricing to the charging operation of EVs.

Reference	Strategy	Demand simulation	Electric grid simulation	Contribution
Canizes et al. [2019]	Decentralized LMP		Smart City mockup model, incluiding the agent-based demand simulation and the OPF formulation of the electric grid	Agents charge in one of the available parking lots provided with charging infrastructure. The LMP of energy at the lots is quite efficient in decreasing the price paid for the energy, even if does not count for different weekdays variations.
Liu et al. [2018]	Centralized LMP	Danish EV historical data	OPF	Maximizes social welfare, efficient by relocating demand over time.
Luo et al. [2018]	Decentralized LMP	The demand at stations is simulated by means of a linear regression model.	OPF + Stochastic Dynamic Programming	Focus on the profit maximization of the charging infrastructure provider, by relocating demand in time and space (buying cheaper than the sell price of energy).
Tang and Wang [2016]	Decentralized LMP based on 4 price periods (TOU)	Probabilistic ABM	PF	Inter-node movement of the EVs is very effective in alleviating the load peaks (space relocation). Establishes a relationship between traffic and power flows.

Xydas et al. [2016]	Centralized LMP	Multi-Agent System (Schedule Queue)	Hardware-in-the-loop	Both the network and the agents benefit from the centralized control architecture, decreasing the price of energy.
This thesis	Decentralized LMP	Probabilisitc agent-based model (Monte Carlo simulation method)	OPF (MATPOWER)	• Real-time coordination between the electric grid and the agents aggregator. • Simulation over several days, accounting on the variable cost of energy in the system. • Responsive: agents are defined individually, each of them taking decisions in accordance to their own charging preferences and goals.

As can be seen from table 2.4, most of the previous studies that have implemented LMP to the charging operation of EVs, use OPF to model the electric grid response, and most of them identify with a decentralized control scheme. Nevertheless, none of them consider charging along the way, as they mostly focus on choosing a charging station near the destination of the agent, or at home. Also, the modelling of the agents is most of the times done through general tendencies (linear regression models or EV historical data), but do not analyze the interaction and interdependence of the multiple agents in the system. Only in Canizes et al. [2019] and Tang and Wang [2016] they do consider agents as individual entities that are responsive and interact in the system.

The modelling of the agents in this thesis will be discussed in the next section.

2.6 Agent-Based Modelling

With the purpose of assessing the responsiveness of agents to the economic signals sent by means of smart pricing in the operation of charging EVs, we need a simulation environment where the behavior of agents can be reflected. We are presented with three main methods in use (Maidstone [2012]):

- Discrete Event Simulation (DES)

  In Operational Research, DES is probably the most common method of simulation. The model consists of entities, events and resources. Entities are the objects moving through the system, events are the processes through which the entities pass, and resources are the objects needed to trigger these events.

  Entities enter the system and take several states before leaving, so the system can be though as a network of queues and servers. If we wanted to simulate the behavior of agents using DES , it would be necessary to establish all possible states through which the agent can pass, and define their behavior accordingly.

- System Dynamics (SD)

  System Dynamic models are only slightly different from DES models, as they focus on the flows around the network and not on each of the agents (entities). In SD models, three types of objects are taken into account: stocks, flows and delays. Stocks are the stores of objects, flows define the movement between stocks, and delays are the time between the system measuring a state and acting on it.

  If we were to model the behavior of agents under the premises of SD, we would focus on the number of agents charging at each station (stocks), the movement of agents between locations (flows), and the delays of the system between the computation of the grid status and the clearing of the locational marginal price. It would be convenient to use this model if we had realistic data on the flows of the drivers in a given space, like for example the bike sharing systems in a city, for which we know the number of bikes at every station, and all trips taken with them.

- Agent-Based Modeling (ABM)

  ABM is a quite new method, and the main difference with the others is that agents are defined as autonomous (self-directed), with a series of predefined rules to achieve their objectives and while interacting with the rest of agents in the system.

ABM has evolved from Cellular Automata (CA), which have been present since the beginning of computing. CA were first mentioned by John Von Neumann in the 1950s, and they became popular after the publication of The Game of Life by John Conway in the 1970s (Games [1970]). The complexity of this cellular automaton came from the rules it uses to convert the knowledge of states in the neighbouring entities to determine the next state. We could say ABM includes notions of game theory, complex systems, computational sociology, multi-agents systems and evolutionary programming.

The main potential of this type of models is the asynchronous interactions among agents and between agents and their environment, meaning they do not all change states at the same time but interact in the longer time frame (Castiglione [2006]). Moreover, ABM allows a great richness of detail in the behavior (predefined rules) of each agent in the system, which can shed light into emerging phenomena, irreducible to simple trends.

For these reasons, ABM will be the model used in this thesis, allowing us to simulate a range of different agents, each of them with varied treats personality features and with different charging behaviors. ABM will show responsiveness phenomena that we wouldn't be able to simulate otherwise, by only considering general trends.

ABM models are not difficult to start coding, and very easily scalable, as we only have to define how the features are distributed among the population to introduce the randomness of agents, and all of them will share the same structure only with different rules to follow. This has become possible due to the rise of Object Oriented Programming (OOP). Under OOP, we will be able to define types of objects (for instance, agents, EVs, or charging stations) who have a predefined structure and a portion of code defining their behavior in the system. For an agent, he will be assigned a home location, a working location, a car, and behavioral parameters indicating its range anxiety or willingness to pay, among others. For a car, the main features to define the object class, would be the battery, the consumption or the discharge profiles.

Object Oriented Programming can be coded in several of languages, such as JAVA, Python or C++. In this thesis, JAVA language has been chosen for its good compatibility with Matlab, which we will use to complement the agents model with the grid model, as explained in section 3.

2.6.1 Monte Carlo Simulation Method

The features of the objects in the system can take a range of values, defining their properties and behavioral rules. Defining how these features are distributed among the population is an important part of creating a realistic model in ABM . For instance, take the home location of agents (EV drivers). The areas of the city within which the agents live are known, and so are the density of population in each of them. If we are to simulate a set of agents in the city, we would random rolls to assign a larger number of agents to those more populated areas of the city, and vice versa. In other words, we are looking for a way of generating randomness across a set of agents, but intentionally creating a realistic model where some options are more probable than others. The way to simulate such sets is the Monte Carlo Simulation method.

The Monte Carlo simulation model uses randomly-generated numbers to simulate the behavior of a situation (Fox and Burks [2019]). Assigning a probability disrtibution (theoretical or empirical) to the random variables, the resulting model will be within a realistic range. Therefore, if we generate random numbers to simulate behavior of the objects within the ABM at issue, they will later be assigned a range and a consequence (event).

$$Random\,number \longrightarrow Assignment \longrightarrow Event$$

We can illustrate this with an example later used in this thesis, like assigning a minimum desired SOC level for each agent. If X defines the random variable representing the minimum SOC desired by the agent (%):

- Assign a probability distribution to the random variable at issue, X. If, among the population observed, we see an uniform distribution of values between 40% and 100%:

$$X \sim \mathscr{U}(0.4, 1) \tag{2.7}$$

  For which the mean is $\mu = \frac{1}{2}(0.4 + 1) = 0.7$ and the variance $\sigma^2 = \frac{1}{12}(1 - 0.4)^2 = 0.03$.

- Generate a random number between 0 and 1 (denoted Y,), and assign intervals in which this number represents each of the possible events, according to the previously-defined distribution:

$$X = 0.4 + Y(1 - 0.4) \tag{2.8}$$

- Produce a number of n trials (number of agents in this case), which corresponds to a series of $X_1, X_2, ..., X_n$ independent identically distributed random variables. For this set, let $\overline{X} = \frac{\sum_{i=1}^{N} X_i}{N}$ be the average of the sample, then the CDF of the function $Z_n = \frac{X-\mu}{\sigma/\sqrt{n}}$ converges to the standard normal CDF at all points.

The Central Limit Theorem allows us to work with any distribution, stating that the mean of a sample is normally distributed independently of the type of distribution the data is taken from. Being Φ the level of precision, s the standard deviation of the sample:

$$P\left(-\frac{\Phi}{s/\sqrt{n}} \leq \frac{\overline{x}-\mu}{s/\sqrt{n}} \leq \frac{\Phi}{s/\sqrt{n}})\right) = confidence\, level \tag{2.9}$$

If the desired confidence level is 95%, from the table of the area under the normal curve, we can obtain the bounds of equation 2.9, and these are -1.96 and 1.96 respectively. By these means, we can calculate the minimum sample size to achieve a given precision and confidence level with the formula:

$$\frac{\Phi}{s/\sqrt{n}} = 1.96 \tag{2.10}$$

For the example at issue, if we want a precision in the sample average of 5% (indicating the average of the sample will be wihin a 5% difference of the variable mean, $\mu = 0.7$ and a confidence level of 95%:

$$\Phi = 0.05 \cdot (1-0.4) = 0.03 \tag{2.11}$$

$$\frac{0.03}{\frac{(1-0.4)^2}{12}/\sqrt{n}} = 1.96 \tag{2.12}$$

Which gives a minimum sample size of $n = 124$.

3 | Model

Local dynamic pricing of charging stations involves the coordination between the fleet of electric cars and their drivers, the charging stations, and the electric grid to which the stations are connected. Most of the literature focuses on the local distribution of charging to decrease waiting time or maximize its utility, others discuss the benefits of having the charging managed locally at each station to shave the demand peak or reduce losses. However, less literature has been published in the matter of coordinating the smart grid of the city and the price of EV charging at the stations to maximize utility and reduce the social cost of charging.

In order to study the feasibility and potential benefits of integrating a responsive interaction between the charging stations and the grid, a cooperative model between the two has been built in this thesis. The boundaries of the model lie on the limits of the distribution grid, and takes the price of energy from the transmission grid as reference for the control of the operation (LMP). Therefore, the aggregator (control unit) is placed between the transmission and the distribution grids.

Whereas solar panels and batteries are gaining great relevance in the smart grid, this model will not consider local power generation or storage (other than the batteries of the vehicles). Nevertheless, they will undoubtedly play a pivotal role in the optimized operation of the grid and should be the matter of future research in this topic of local dynamic pricing.

The main components that this study will therefore involve are the residential consumption and the charging stations for electric vehicles (see Figure 3.1). The subject of study is the price control and that is why there will be bidirectional information flow between them and the controller. The controller, aware of the price of energy from the transmission grid and the consumption in the distribution grid, has the role of issuing economic signals with the purpose of optimizing operation at the scale of the city.

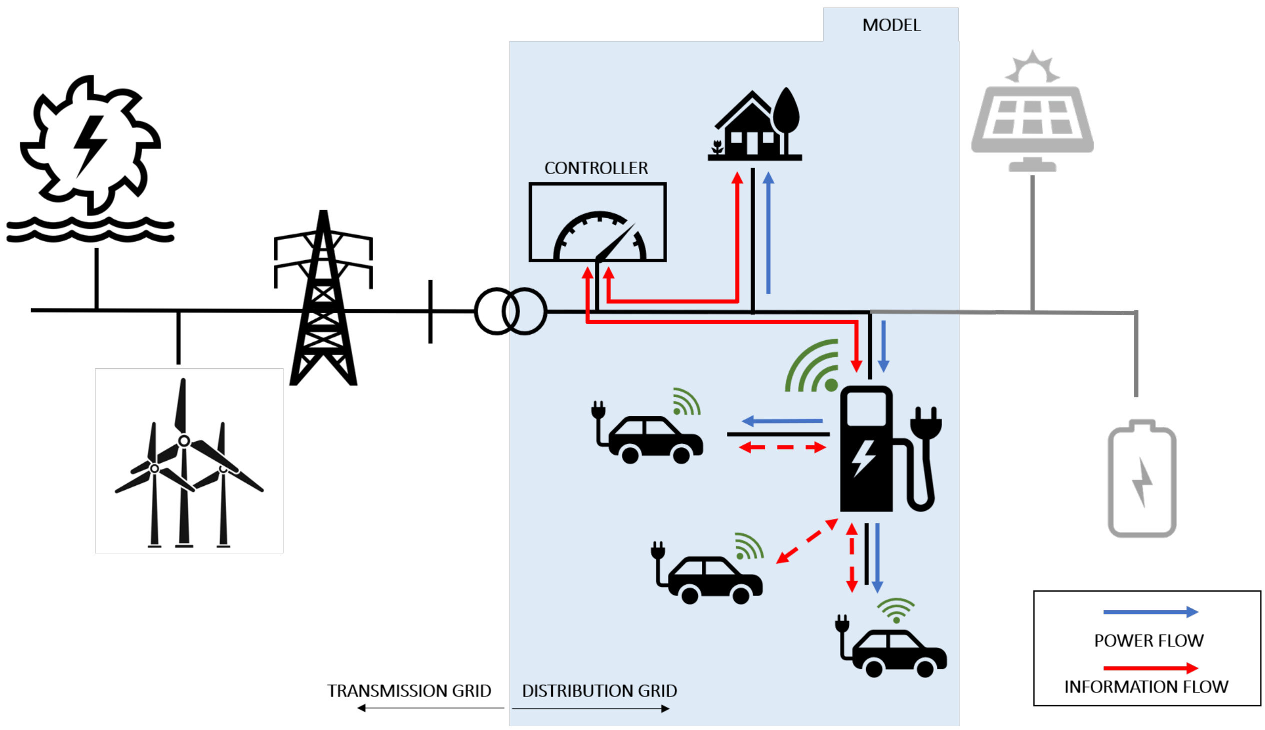


Figure 3.1: Model

The price taken from the transmission grid can be more or less variable depending on the energetic mix at issue. For instance, 98% of the electrical consumption in Norway comes from hydroelectric power (IEA [2017]), and even if the price can vary throughout the year, it is normally stable within the day (AS [a]). On the contrary, the Danish coal consumption has been drastically reduced (specially from 2006) to rely on the growing wind power installed in the country. Wind power generation can be much more volatile and so are the prices of energy in Denmark, significantly in the easter regions (Sealand and Capital regions, DK2 in AS [b]). For this reason, the controller of the model will take the energy price as reference to control and improve the local operation.

The second signal introduced in this control unit will be the local consumption within the distribution grid. Its role is to reduce demand peaks and combine the demand flexibility with the fluctuations in the energy supply price. With the deployment of smart grids, it is possible in this sense to actuate on a specific bus of the local grid, which comes to the scale of a specific charging station in this study.

3.1 Computational overview

Computationally, there will be two models working in parallel (see Figure 3.2):

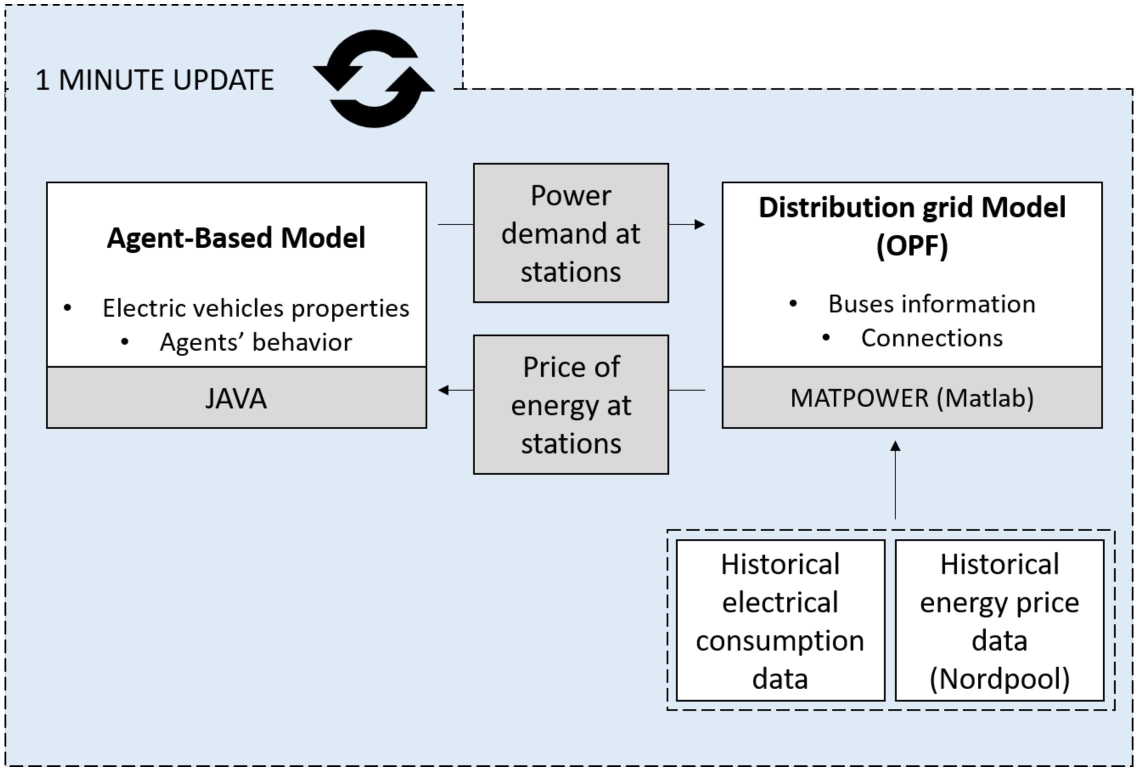


Figure 3.2: Computational model

- On the one hand, there will be the Agent-Based model of the agents' behavior. This model accounts for the population of electric vehicles in the city and all the attributes of their drivers' preferences and journeys.

  This model will be implemented in JAVA for the suitability of this language for object-oriented programming. We can easily reproduce a population of different electric vehicles and drivers by inheriting the properties of a general definition of these classes.

  The code of this ABM model is present in a public GitHub repository (**?**), and a brief description of its use in Appendix A.

- On the other hand, we find the grid model containing all connections between the buses in the distribution grid and the all their electrical information (consumption, voltage angle, losses, etc.).

  AC optimal power flow (AC-OPF) is a non-linear, non-convex optimization problem of the flow within the distribution grid. It can be done by means of very different optimization software that implement the equations of OPF (see section about OPF). For the great synchronous compatibility between JAVA and Matlab (MATLAB [2019]), we have chosen to use the MATPOWER package in

Matlab to compute the OPF in the grid.

In order to make this model responsive, fast enough to account for the demand and supply of power, a response time of 1 minute has been established. This update interval should be shorter in a real-life control of the power demand, but has been set to 1 minute due to computational limitations.

In order to feed the model with realistic data of both the energy price (from the transmission state grid) and the local consumption at each bus of the distribution system, two data sets are included:

- First, the electric hourly-consumption per bus in the grid, from a 2012 historical data repository of the power company serving this city (Lillebo et al. [2019]). The 2^{nd} of February 2012 was the day with the highest consumption in record, and is therefore used in this thesis for a worst-case scenario of the grid constraints.

- Second, the hourly energy price from the Nordpool Day-Ahead Market Price (Nordpool, 2020). In this database there is no hourly record before January 2018, and for that reason the model considers the prices for the period of the 8^{th} to the 22^{nd} of January 2020. The period has been chosen in winter for its similarity in consumption and price tendency, but also intentionally for the volatility in the energy prices (see Figure 3.3 at the DK2 zone: East Denmark. Nordpool, 2020). The purpose is to illustrate the efficiency of the proposed control method when adjusting the power demand to the supply prices.

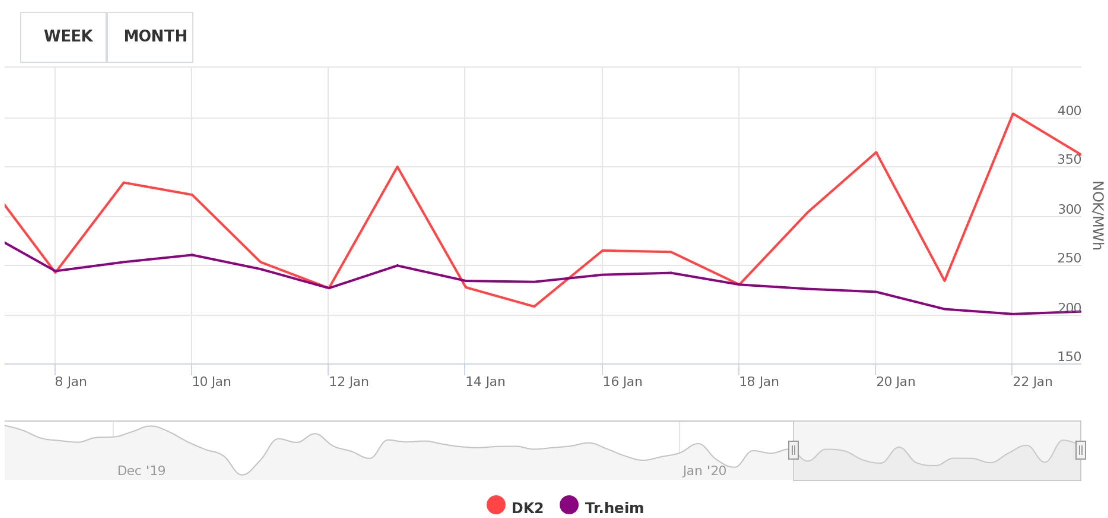


Figure 3.3: Prices in the TRD and DK2 zones for the period of January 8th-22nd, 2020 (Nordpool, 2020)

3.2 Geographical extension

In this work, we have taken Steinkjer, a middle-sized city in the county of Trøndelag (Norway) as the case of study, because of the grid data availability. To illustrate the study, a data model in GIS has been implemented to include and locate all stakeholders in the system.

Figure 3.4: Steinkjer in the map

The first would be to identify the bounds of the city and the use of each area within. To do so, we have used the *Arealbruk WMS* map provided by GeoNorge, the national database site for geographically located information in Norway (Geonorge [2019]). This map, updated in 2019, divides land use into 13 different categories, such as residential buildings, green spaces or leisure buildings. For the city at issue, figure 3.5 shows the use of the different spaces in the territory considered.

In our computational model of the city, it is more convenient to divide geographical areas as rectangles, as we can easily identify in which area a point is located by knowing its coordinates and the vertex (bounds) coordinates of the areas. For this reason, the bounds of city form a square (see Figure 3.6.a).

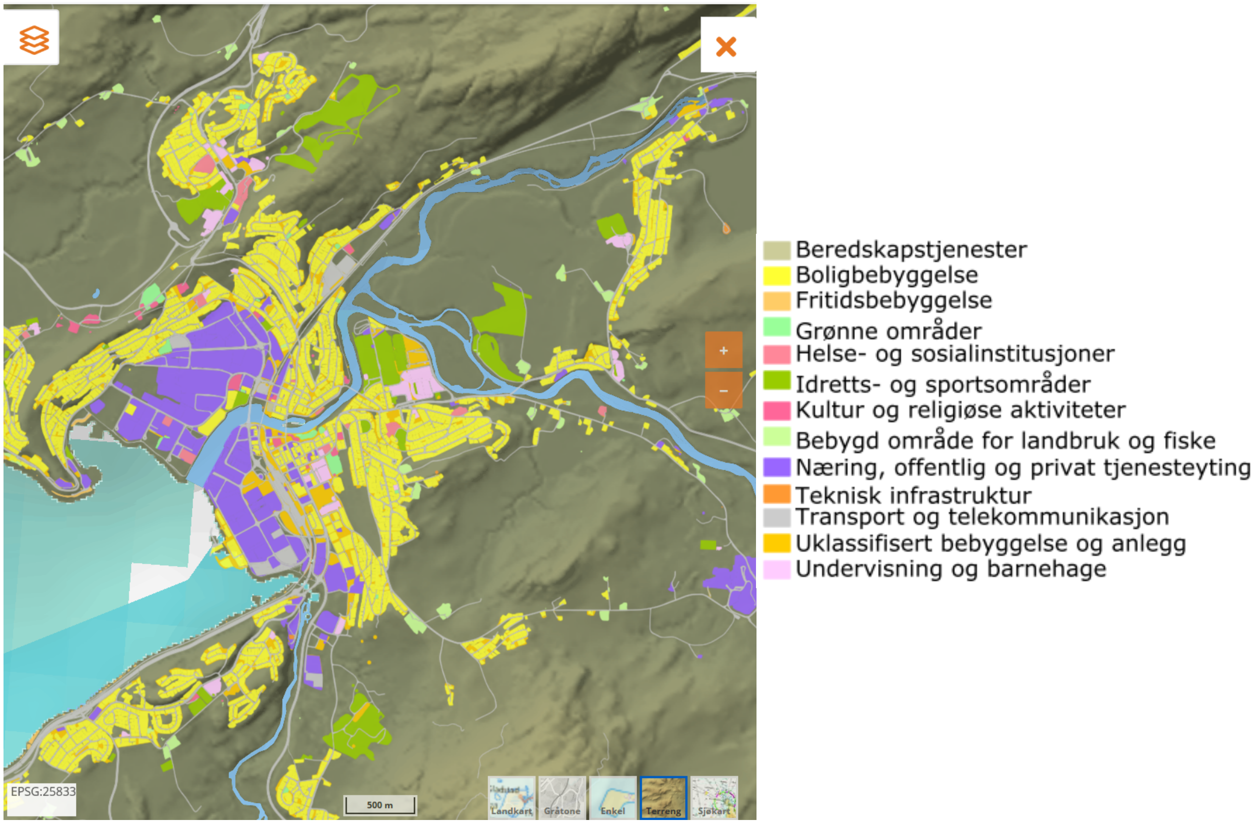


Figure 3.5: Land use in the city at issue (Geonorge [2019])

The same process has been followed to identify residential and working areas in the city. Working areas have been divided into four rectangles in the city centre (Figure 3.6.b) according to the land use map. Residential areas are three stripes where there is urbanization in the territory (Figure 3.6.c).

(a) City bounds

(b) Working areas

(c) Residential areas

Figure 3.6: City bounds and land use divisions

3.3 Electrical grid

For this city, we have available not only the distribution grid layout for the medium and low voltage lines, but also the consumption per bus during a whole year. This data will allow us to calculate the cost of energy at the load for each bus of the system, and therefore obtain the price that charging incurs into at each station located in the city.

The system consists of 974 buses, 1 slack bus (feeder to 66 kV, upstream network) and 1 PV bus (hydropower station). The buses are connected to the distribution grid, either to the medium voltage of 22 kV or to the low voltage 400 V/230 V. A complete diagram of the system, based on electrical distance metrics (Cuffe and Keane [2017]), can be appreciated in Figure 3.8.

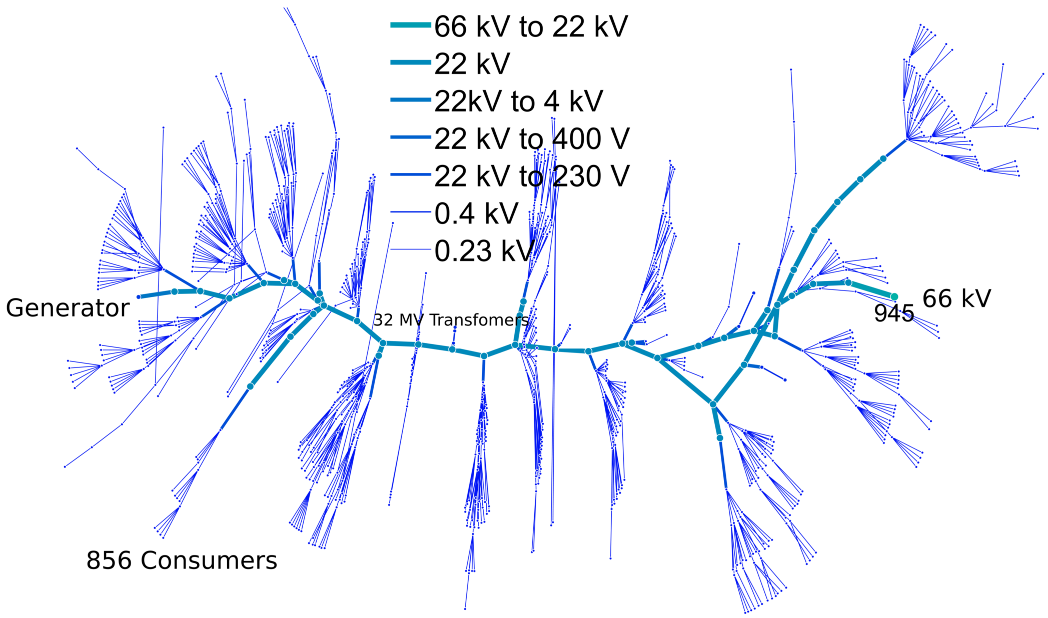


Figure 3.7: Electrical grid diagram, based on electric distance metrics

For the sake of locating the MV/LV transformers in the city, and with the purpose of later connecting the charging stations to the buses they represent, a map layer of these transformers 22 kV/ 0.4 kV has been added to data model in GIS, as illustrated in Figure 3.8.

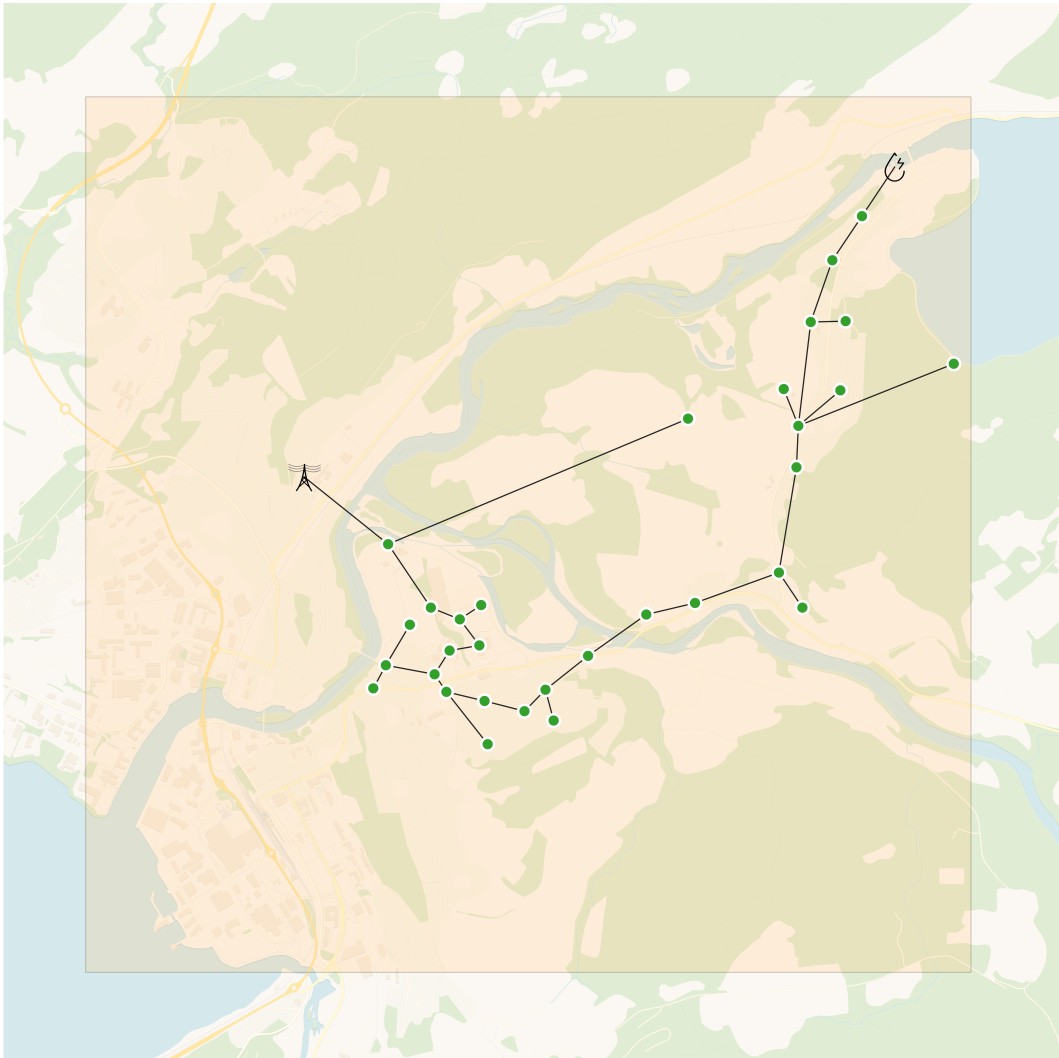


Figure 3.8: Location of MV/LV transformers in the city, the 66 kV feeder (upstream network) and the hydropower station

3.3.1 MATPOWER Model of the Grid

As mentioned before, the software used in this thesis to compute the OPF problem in the distribution grid will be MATPOWER (Zimmerman and Murillo-Sánchez [2019]). By means of this package, we can modify and augment the problem formulation by reusing the portions of interest (Zimmerman and Murillo-s [2019]).

The input data for MATPOWER is given in a "MATPOWER Case", which is a file containing the matrices in a Matlab structure. This structure is referred as `mpc`, and in the case of study, it mainly includes the content presented in table 3.1. The original data from the grid operator was converted into a MATPOWER case by the Electricity Markets and Energy System Planning (EMESP) [1] of the Norwegian University of Science and Technology. The methods and outcomes of building this case were presented in their conference paper (Zaferanlouei et al. [2017]) [2].

Table 3.1: Fields describing the distribution grid details in a MATPOWER case file

<table>
<tr><th>Field</th><th>Description</th><th>Value in the case of study</th></tr>
<tr><td><code>mpc.baseMVA</code>
<code>(Scalar)</code></td><td>System MVA base to convert all magnitudes into per unit quantities.</td><td>25 MVA</td></tr>
<tr><td><code>mpc.bus</code>
<code>(Matrix)</code></td><td colspan="2">
<table>
<tr><th>Column</th><th>Description</th><th>Value</th></tr>
<tr><td>1</td><td>Bus number</td><td>1-974</td></tr>
<tr><td>2</td><td>Type</td><td>972 PQ buses + 1 PV bus (Hydropower) + 1 Slack bus (upstream network)</td></tr>
<tr><td>3</td><td>Real power demand in MW</td><td>Historical power demand data + charging stations demand</td></tr>
<tr><td>4</td><td>Reactive power demand in MVAr</td><td>Historical power demand data</td></tr>
<tr><td>10</td><td>Base voltage (kV)</td><td>0.23/0.4 kV in low voltage, 4 kV in the hydropower station bus, and 66 kV in the upstream network connection bus</td></tr>
</table>
</td></tr>
</table>

[1] Electricity Markets and Energy System Planning (EMESP) `https://www.ntnu.edu/iel/groups/emesp#/view/people`

[2] In case of requiring the MATPOWER case data, non disclosed in this thesis, please contact the authors, or the author of this thesis

`mpc.gen` (Matrix)	<table><tr><th>Column</th><th>Description</th><th>Value</th></tr><tr><td>1</td><td>Connection bus</td><td>Buses to which the upstream network and hydropower station are connected.</td></tr><tr><td>2</td><td>Real power output (MW)</td><td>0 (unlimited) for the upstream network, 1 for the hydropower station.</td></tr><tr><td>4-5</td><td>Maximum and minimum reactive power generated (MVAr)</td><td>[-300,300] for both.</td></tr><tr><td>9-10</td><td>Maximum and minimum real power output (MW)</td><td>[0,100] for both.</td></tr></table>
`mpc.branch` (Matrix)	<table><tr><th>Column</th><th>Description</th><th>Value</th></tr><tr><td>1</td><td>"From" bus number</td><td></td></tr><tr><td>2</td><td>"To" bus number</td><td></td></tr><tr><td>3-4</td><td>Resistance of reactance of the line</td><td>Taken from the grid data provided by the serving power company.</td></tr><tr><td>6-8</td><td>MVA rating (long, short and emergency)</td><td>Depends on the cable type of each branch. See Table 3.2 for detail values of the cables used in this grid and their MVA rating.</td></tr></table>

	Column	Description	Value
`mpc.gencost` (Matrix)	1	Model	Piecewise linear model
	4	Number of data points to define price	2: The price of energy is linear and proportional to the energy price given by the transmission state grid.
	5	Cost	Price introduced by the historical data of Nordpool.

Regarding the MVA rating of the branches (within the `mpc.brach` part of the structure), they are derived from the type of cable used in each connection, which is given by the data provided by the power company. Using the Norwegian Electrotechnical Comittee standard (NEK 400:2018), we can obtain the ratings from the cables' isolation type, cross-sectional area and the conductor material. The formula to use is hereby presented and so is the table summarizing the cables used in this grid and their MVA rating (Lillebo et al. [2019]):

$$MVA_{rating} = \frac{\sqrt{3} \cdot I_{cap} \cdot V_{Phi}}{1000000} \tag{3.1}$$

Where I_{cap} is the current-carrying capacity of the cable, and V_{Phi} the phase voltage.

Table 3.2: Cable types used in the distribution grid and their MVA rating (Lillebo et al. [2019])

Cable code number	Isolation type	max A	MVA Rating
PFSP 1X3X25 AL	PVC	69	0.0275
PFSP 1X3X50 AL	PVC	99	0.0394
PFSP 1X4X50 AL	PVC	99	0.0394
TFSP 1X3X150 AL	PEX	220	0.0876
TFSP 1X3X240 AL	PEX	290	0.1155
TFSP 1X3X95 AL	PEX	172	0.0685
TFSP 1X4X16 AL	PEX	64	0.0255
TFSP 1X3X50 AL	PEX	117	0.0466
TFSP 1X4X95 AL	PEX	172	0.0685
PFSP 1X3X10 CU	PVC	54	0.0215
PFSP 1X3X16 CU	PVC	70	0.0279
PFSP 1X3X2.5 CU	PVC	24	0.0096
PFSP 1X3X4 CU	PVC	33	0.0131
PFXP 1X4X16 CU	PVC	70	0.0279

3.4 Charging stations

In the model, the charging stations also have to be placed and specify which bus of the grid they are connected to. In the city at issue, the actual total count of charging stations is 8 (NOBIL), which is not enough to simulate a scenario where the penetration of EV is as predicted. In addition, all except for one of these stations are placed outside the bounds of the electric grid we have available data of. Therefore, a new set of stations has been created to simulate a more friendly environment for the charging of electric vehicles. With a population inferior to 25.000 inhabitants, and according to the forecast of EV penetration, we have placed 15 stations among the most probable places where they could be located, both in public facilities and busy paths of the city (Lorentzen et al. [2017]).

Fast charging stations can sometimes be connected to existing MV/LV transformers if the transformer has sufficient capacity and the voltage level is adequate (400 V TN network). However, most of the times they are connected to the grid by means of a dedicated transformer (see Figure 3.9) without any additional charge (Sørensen et al. [2018]), and since the model will grant a maximum charging power of 150 kW to the stations, they will all be placed after a dedicated transformer. For the case of study, we will only consider stations that comply with the Mode 4 of the standard defined by the International Electrotechnical Comission (IEC 61851) in Part 1. Under this standard, the connection of the EV to an AC or DC supply network must utilize a DC EV supply equipment.

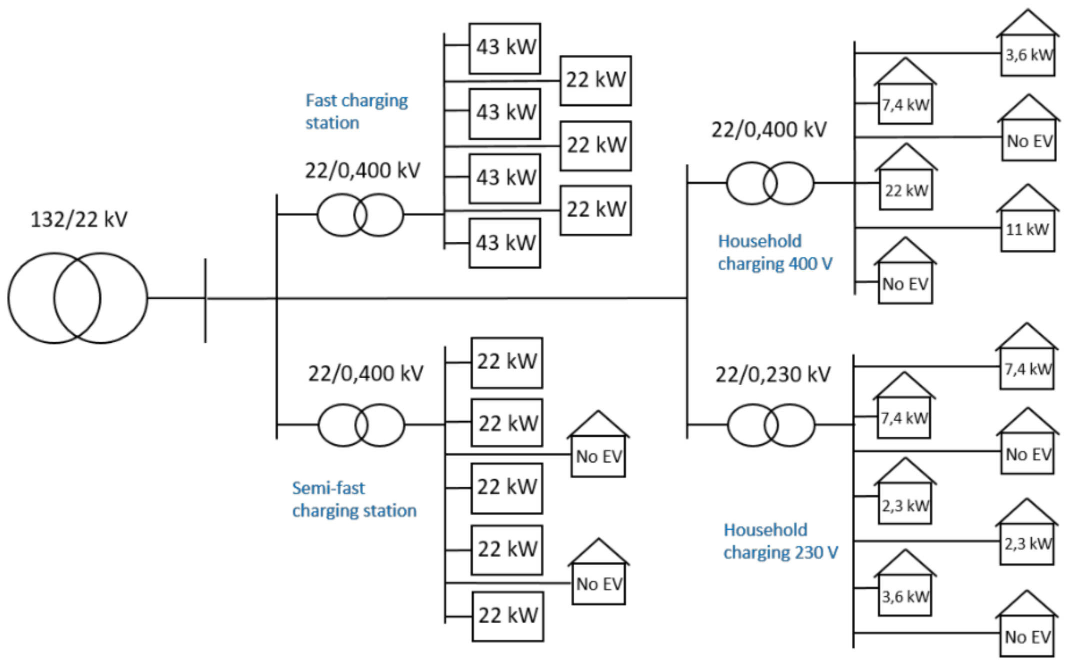


Figure 3.9: Grid connection of charging stations (Sørensen et al. [2018])

DC chargers can either be connected to a portion of the grid that is already in DC (common DC-bus configuration, less common) or to the AC grid by means of a rectifier. In this model, only the second configuration will be considered, where the conversion from AC to DC is done at each station. Under Part 23 of the same standard (IEC 61851), we can also find the typical configuration of DC charging systems and their connection to the AC grid. As the most used DC-fast chargers have an efficiency of over 93% (Ronanki et al. [2019], the model will be simplified by not adding an extra stage but simply introducing the power demand at the specified bus of each station.

In order to simplify the allocation of the stations, we will consider the stations and their transformers are placed next to one of the existing connection points to the 22 kV (MV) lines.

Therefore, 15 of the existing 22 kV connection points will be assigned a charging station with 2 connection points each. The resulting layer of the data model in GIS is represented in Figure 3.10. In the coordinated model that comprises both the stations and the grid buses, the consumption at each station will be assigned to the bus corresponding its MV connection point.

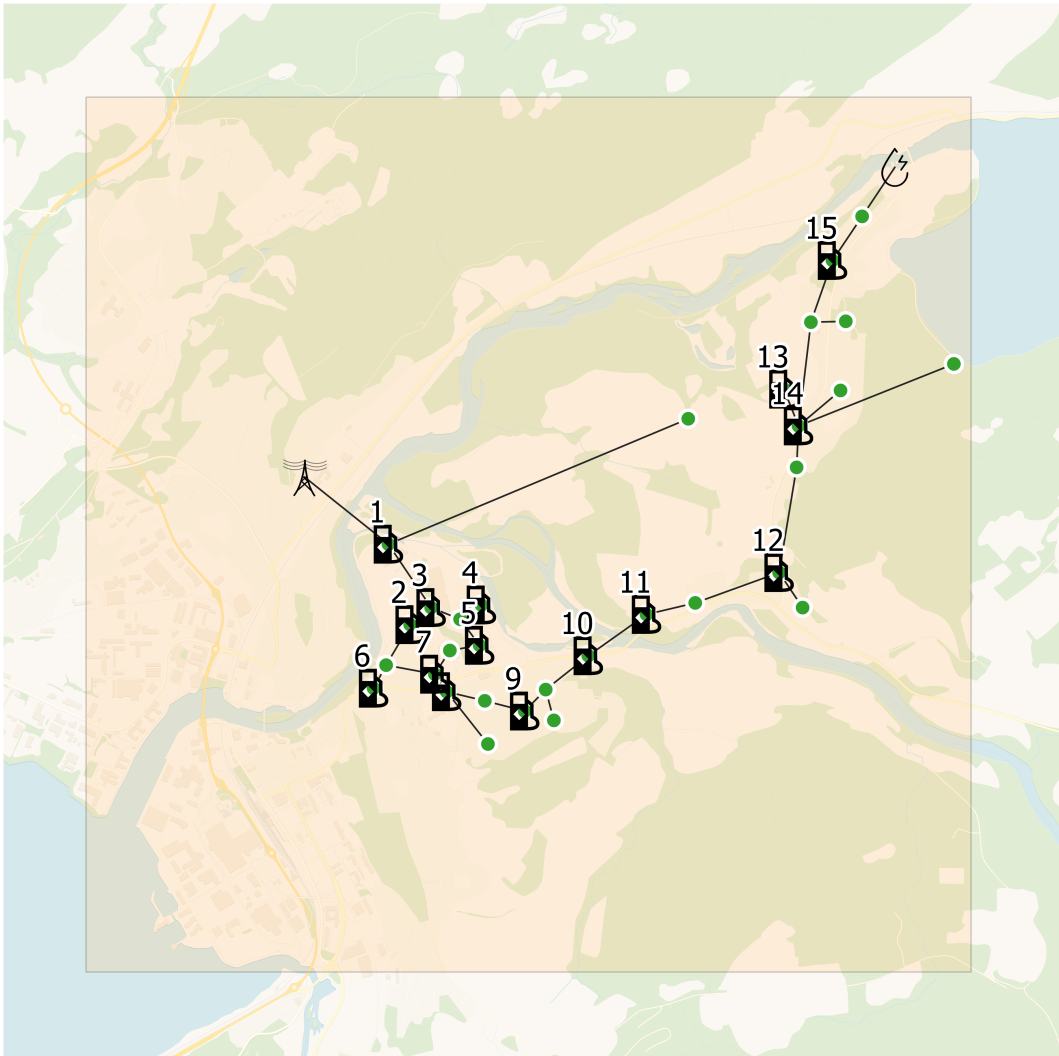


Figure 3.10: Location of the 15 charging stations in the city, and their ID number in the model

3.5 Agents

The key of Agent Based Models is the singularity of each one of their agents. The model does not compute overall tendencies, but simulates the actions of autonomous agents who make decisions on their own preferences to accomplish goals. Agent Based Models can therefore shed light into emergent phenomena, which is the objective of our study on local dynamic pricing of energy among the charging stations.

We can start by looking at the `Agent` class attributes and the values they take in this model. Then, we will analyze in detail the behavioral parameters they are assigned in the simulations.

3.5.1 Agent Class attributes

An agent in this context represents an EV driver with a number of attributes and behavioral parameters. The way agents are modeled and how they interact with the rest of the model at issue are taken from the preceding master thesis of Eilertsen [2013]. In his work of integrating the EV in the software of smart grids, the agent is an object class included in the overall model as illustrated in Figure 3.11.

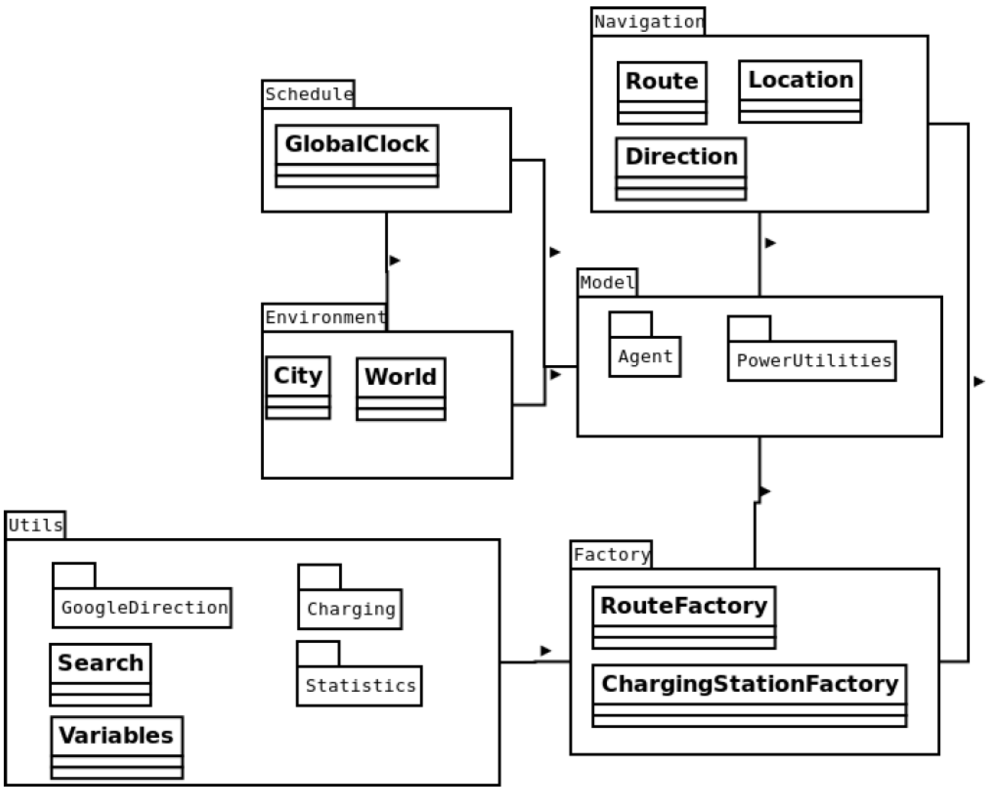


Figure 3.11: High-level overview of the agent class integration in the model developed by Eilertsen [2013].

We can see the agent class is within the Model package, and connected to the Navigation, Environment, and Schedule packages. When looking in detail at the structure of an agent, it has a number of attributes, and is connected to a Car object class (see Figure 3.12).

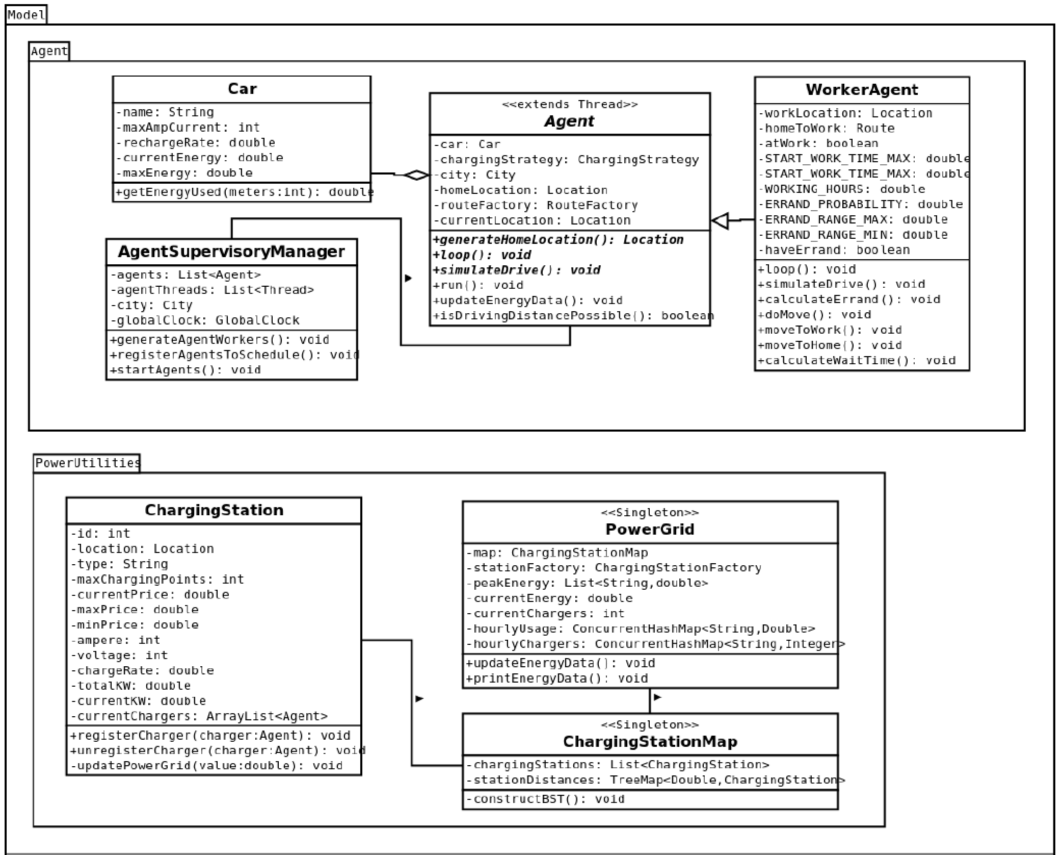


Figure 3.12: Detail view of the Model package and the Agent class Eilertsen [2013].

Inherited from the `Agent` class, we have the `Worker Agent` class, which is an agent to which we assign a work location and working hours. The `Worker Agent` class will define all the agents simulated in the model of this thesis, controlled by the `Agent Supervisory Manager` that relates the actions of the agents with the rest of the model (the global clock, the city properties, etc.).

In turn, the `Car` class has a number of attributes as well. A car is defined in the model from its type, recharge rate, current SOC and maximum battery capacity. Three models of car will be used in this thesis, taken from the three most common ones in Norway (Sørensen et al. [2018]).

With the purpose of describing how agents and their cars integrate the model, we can summarize their attributes in Figure 3.13 and Tables 3.3 and 3.4.

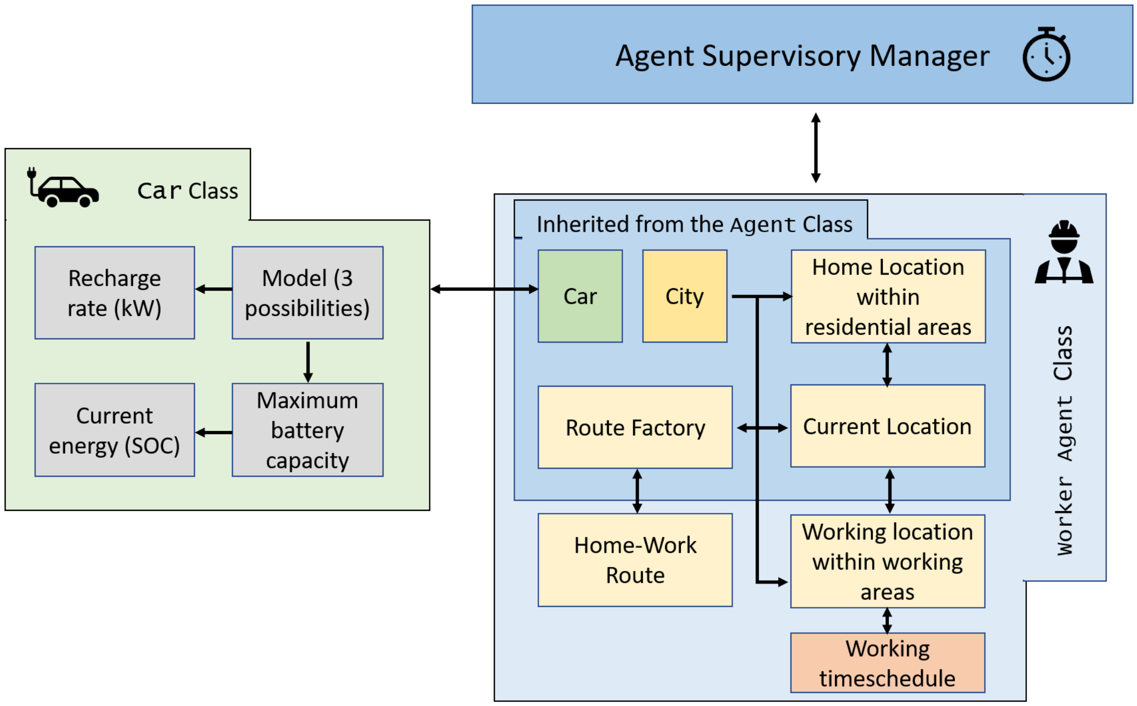


Figure 3.13: Main attributes of the `Worker Agent` and `Car` classes.

Table 3.3: Worker Agent attributes and their values.

Attribute	Value
Car	Randomly assigned car of the possible models (See Table 3.4)
City	All agents belong to the city at issue
Home Location	Randomly generated location within the residential areas
Work Location	Randomly generated location within the working areas downtown
Home-Work Route	OSMR Route generated between the locations above (Luxen and Vetter [2011])
Current location	Either at home, at work, or at any intersection of the home-work route
Working time schedule	Randomly generated work start and end times. Start times range from 7:00 to 8:00 AM, and the end times are calculated 8 hours later

As mentioned before, the worker agents can be assigned one of the three most common EV models in

Norway (elbil.no), which are:

Model	Consumption Rate [kWh/km]	Charge rate [kW]	Battery Capacity [kWh]
Nissan Leaf (Nissan-Norge [2019])	0.167	50	40
Tesla S (Tesla-Norge)	0.198	150	100
Volkswagen e-Golf (Volkswagen-Norge [2018])	0.166	50	35.8

Table 3.4: EV models and their attributes.

In this study, agents make two trips per day (home to work and back), and the distance travelled per trip is between 1.5 (imposed minimum route distance) and 4.5 km (maximum distance within the city bounds). As it can be appreciated in Figure 3.14, the maximum distance travelled by agents from residential areas (in red) to working areas (in green) in the city, is around 4.5 km. Therefore, agents in the simulation will be travelling a distance between 3 to 9 km per day, which is not at all realistic according to the Norwegian National Travel Survey 2013/14 (Hjorthol [2014]), where the average distance travelled per day and per person is 47.2 km. Since we only have available grid data for the city bounds specified, the agents have to be restricted within, but we can simulate a longer distance by means of a higher consumption in the vehicles.

In order to solve this shortage in terms of geographical extension, the power consumption of vehicles will be multiplied by 5 in this model, so that daily energy consumption is equivalent to a more realistic travelled distance. Instead of a total daily travelled distance of 3 to 9 km, the consumption corresponds to a distance between 15 and 45 km. The resulting consumption rate for each EV model is given in Table

Table 3.5: Modified EV models and their attributes.

Modified Model	Consumption Rate [kWh/km]	Charge rate [kW]	Battery Capacity [kWh]
Nissan Leaf	0.835	50	40
Tesla S	0.99	150	100
Volkswagen e-Golf	0.83	40	35.8

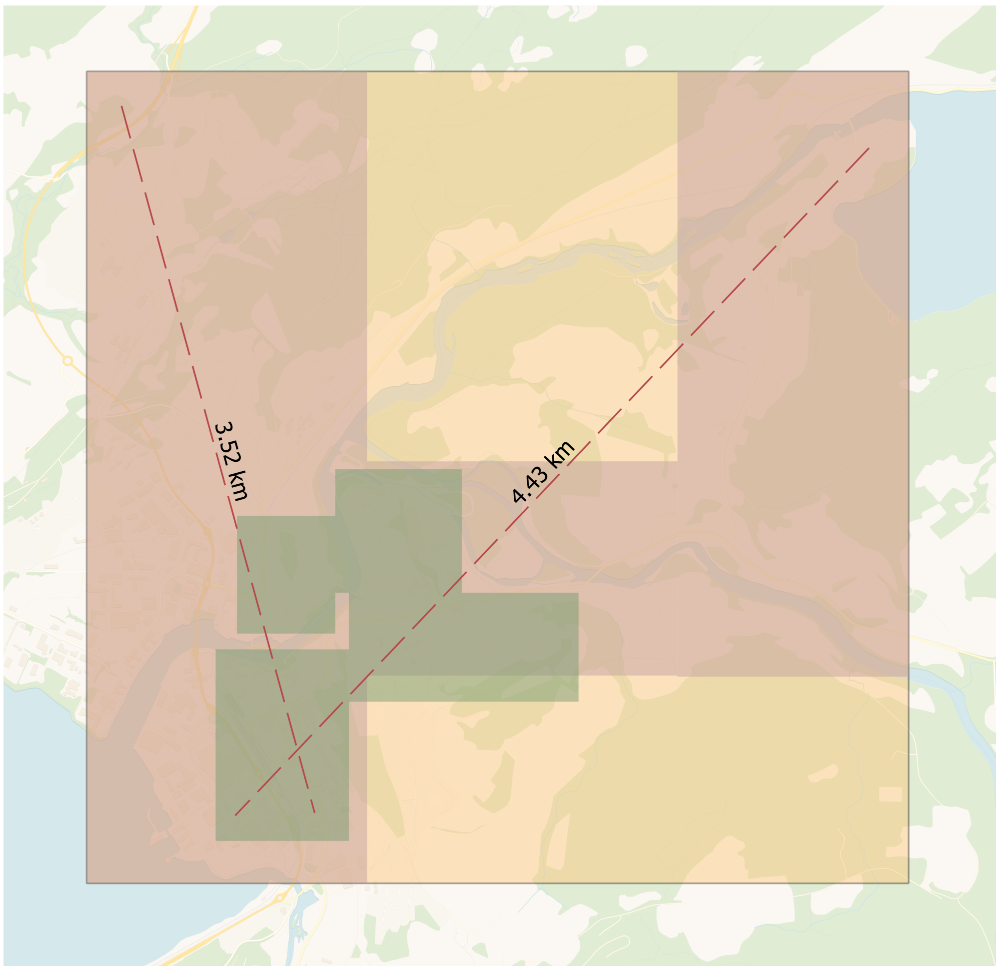


Figure 3.14: Example of the maximum distance travelled by agents between residential zones (red) and working zones (green) in the city.

Consequently, car ranges will be divided by 5 in our model, with the purpose of having a realistic charging frequency, as shown in Table 3.6.

Table 3.6: Real and simulated charging parameters of the EV models

Model	Nissan Leaf		Tesla S		Volkswagen e-Golf	
	Real	Model	Real	Model	Real	Model
Battery capacity [kWh]	40	40	100	100	35.8	35.8
Consumption Rate [kWh/km]	0.167	0.835	0.198	0.99	0.166	0.83
Range [km]	240	47	505	101	215	43
Estimated charge duration [days]	12	12	5	5	4	4

Now that the attributes of a worker agent have been defined, we move onto their behavioral parameters and how they prioritize choices.

3.5.2 Agent behavioral parameters

Many studies that focus on modelling the behavior of the EV drivers from their preferences, use logit models to characterize them (Yang et al. [2016],Wen et al. [2016]). Logistic regression analysis requires collecting data from real users to induce the coefficients, and therefore constitute an accurate manner to predict and simulate behavior. A logit model could predict the most suitable station within a set, as the model takes into account a number of parameters such as the travel time increase, the cost of charging, or the type of road among others.

However, logit models will not be used in this thesis, since they can only infer general coefficients by adding the particular behavior of each agent. Reversing the general trends of behavior to infer the particularities of each agent is highly dependant of the distribution that these parameters follow (Flammini et al. [2019]). Some advocate that assigning the correct parameter distribution to the coefficients of a logarithmic regression model, is particular to each application (Sun et al. [2016]). The distribution is often freely specified by the researcher, and among the most used one can find the normal, log-normal and uniform distributions. For this reason, as there is no logit model already developed that this thesis could relate to in particular, the results of the related work is only useful to identify the main variables that make users choose a station over another.

The most cited variables over which agents decide where to charge are (Yang et al. [2016],Wen et al. [2016],Ma et al. [2019]):

- Baterry state (SOC)
- Travel time (time added in order to include a given station in the way)
- Price of charging

Among the most commonly used methods to characterize agents, we also find the probabilistic models. In this type of model,the probability of an agent taking an action is modelled by means of its preferences and the fit of a situation to its goals. In this case, what has to be modelled for each agent is the strategies they follow to charge their vehicle.

If we base the behavior of the agent on the three above-stated variables, we can build a probability function for each one of them, that will assign a probability of charging to each available station within range, $P_{agent,station} = f(SOC, distance, price)$. One of the variables characterizes the agent's vehicle state (SOC) and the two others, the station at issue (price and distance).

This probability function that will serve each agent to evaluate the whole set of stations available to charge, has to take values between 0 and 1. To make these three variables produce a value within this range, the proposed expression groups the two variables that are station-dependent in the first factor. The second factor accounts for the battery SOC of the agent, that will determine the overall behavior, as indicated in most of the above-mentioned studies. For a set of n agents and m charging stations, the probability of an agent i charging at station j is:

$$P(i,j) = P(i_{SOC}) \cdot P(j_D, j_{Pr}),\ i = 1,...,n,\ j = 1,...,m \tag{3.2}$$

To group both station-dependent variables under the same factor, they need to be weighted. Some studies suggest that the location of the station prevails (for instance, Wen et al. [2016]) and others put the price first (Ma et al. [2019]). Both seem to have a comparable importance, therefore, the model hereby proposed will assign a random weight to each of them between 40% and 60% in this first factor of the probability function. The assigned importance to distance and price (over 1), will be noted x_D, x_P respectively.

The overall probability function for a given agent to charge in a specific station can be rewritten as follows:

$$P(i, j) = P(i_{SOC}) \cdot (P(j_D) \cdot x_D + P(j_P r) \cdot x_{Pr}),\ i = 1, ..., n,\ j = 1, ..., m \tag{3.3}$$

By separating the probability function in several factors, we can study the influence of each variable in the decisions the agents. It is worth emphasizing that each probability sub-function must also take values between 0 and 1 for the overall function to be within range. Hereafter, there is a detail explanation of each of them.

1. **Battery state of charge (SOC)**

   Most of the charging events happen when the SOC of the vehicles of EV owners is between 20% and 80% (see Figure 3.16, Smart and Schey [2012]). Agents will not charge only when the battery level drops below their preferred minimum. They will instead assign a higher probability to charging as the SOC decreases (Harbo et al. [2018]).

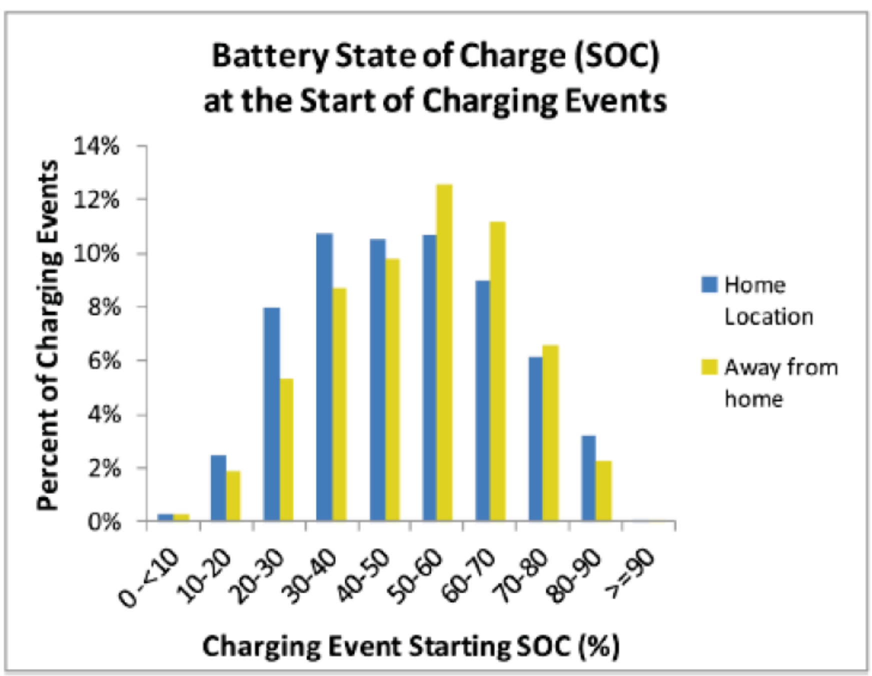


Figure 3.15: Distribution of battery SOC at the start of charging events (Smart and Schey [2012])

Each agent will be randomly assigned a minimum and a maximum thresholds of battery SOC and he will always try to keep his battery level between those. To be realistic, these thresholds will range from 20% to 80% and from 80% to 100% respectively. Agents who prefer depleting their batteries before considering to charge again will have a low threshold of SOC (20-30%), and they will seldom confer any utility to charging when their battery is above a certain level (80%). The opposite kind of agent, the farsighted, will prefer to keep his battery above a high level of charge (50-80%) and will always see some utility in charging (maximum threshold of 90-100%).

In this model, if we only account for the variable of the battery SOC, the probability of charging is zero above the maximum threshold (no utility in charging) and the probability becomes 1 when the SOC drops below the minimum preferred level. Between these two limits, the probability of charging is assigned a linear function for the sake of simplicity. The probability function based on the battery state of charge is as follows :

$$P(i_{SOC}) = \begin{cases} 1, & \text{if } SOC \leq SOC_{min} \\ 1 - \frac{SOC_t - SOC_{min}}{SOC_{max} - SOCmin}, & \text{otherwise} \\ 0, & \text{if } SOC \geq SOC_{max}, \end{cases}$$

An example is illustrated for an agent whose minimum and maximum thresholds are 30% and 70% respectively:

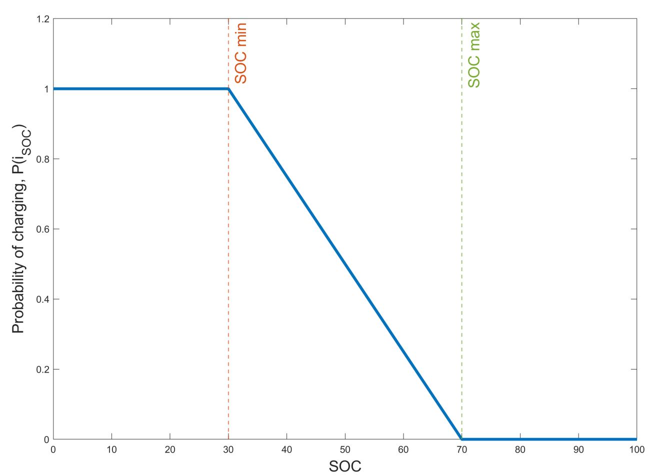


Figure 3.16: Probability of charging in terms of battery SOC for an example agent with thresholds at 30% (min) and 70% (max)

2. **Price of charging at the station**

In Norway, the private companies with the highest share of fast charging stations are Fortum ChargeDrive, Grønn Kontakt and Tesla (Sorensen et al. [2018]). As of today, these companies provide fast charging in over 310, 240 and 60 stations all over Norway respectively. Except for the Tesla Supercharger, the other charging stations are priced upon time and energy consumption altogether. An overview of these prices (as of June, 2020) are summarized in the following Table 3.7 and Figure 3.17.

Table 3.7: Price of energy at the charging station: current situation in Norway. Source: NOBIL

Charging rate	Fortum	Grønn Kontakt	Tesla
50 kW	$2\frac{kr}{min}+2.5\frac{kr}{kWh}=4.9\frac{kr}{kWh}$	$1.25\frac{kr}{min}+2.9\frac{kr}{kWh}=4.4\frac{kr}{kWh}$	$1.7\ \frac{kr}{kWh}$
150 kW	$2\frac{kr}{min}+2.5\frac{kr}{kWh}=3.3\frac{kr}{kWh}$	$1.25\frac{kr}{min}+2.9\frac{kr}{kWh}=3.4\frac{kr}{kWh}$	$1.7\ \frac{kr}{kWh}$

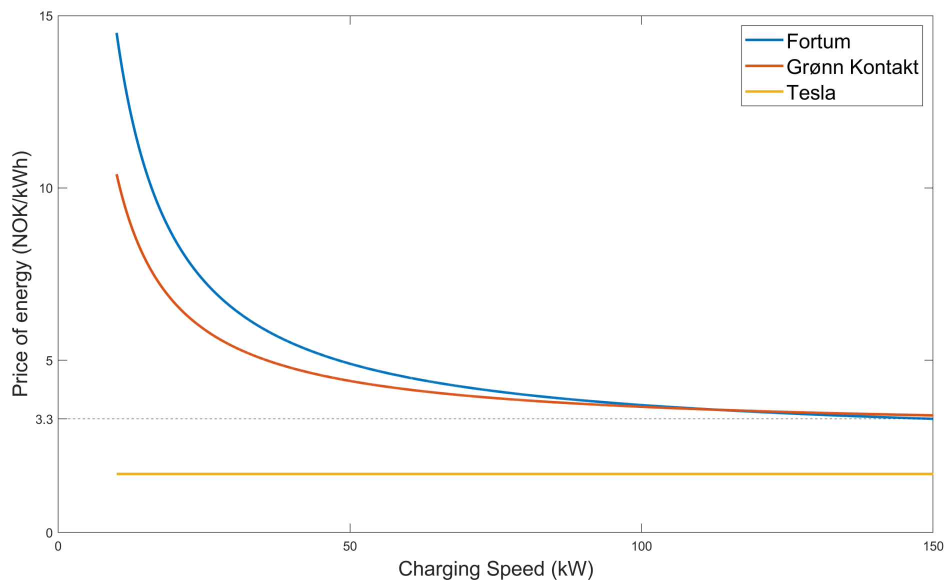


Figure 3.17: Price of energy at the charging station, in function of the charging speed: current situation in Norway .

We can see that the two biggest providers of fast charging for EVs tend to stabilize the price of energy per kWh when the charging speed increases. In the model created in this thesis, as will be presented later in greater detail (see section 4.1.3), the price of recharging will be determined by the energy consumption (kWh) and not by the time of use. However, we will take this limit of 3.3 kr/kWh as reference price for the strategies where the price of charging is static (see section 4).

With the purpose of simplifying the behavior of the agents as a function of the charging price, the probability function of charging is given, once more, by means of a linear function. To do so, a maximum price has to be established, and with the purpose of locally influencing the price, the maximum is set at 10 $\frac{kr}{kWh}$. The agents will assign a probability to charging at a station according to the following function:

$$P(j_{Pr}) = \frac{Price_{max} - Price_{station_j}}{Price_{max}} = \frac{10 - Price_{station_j}}{10}$$

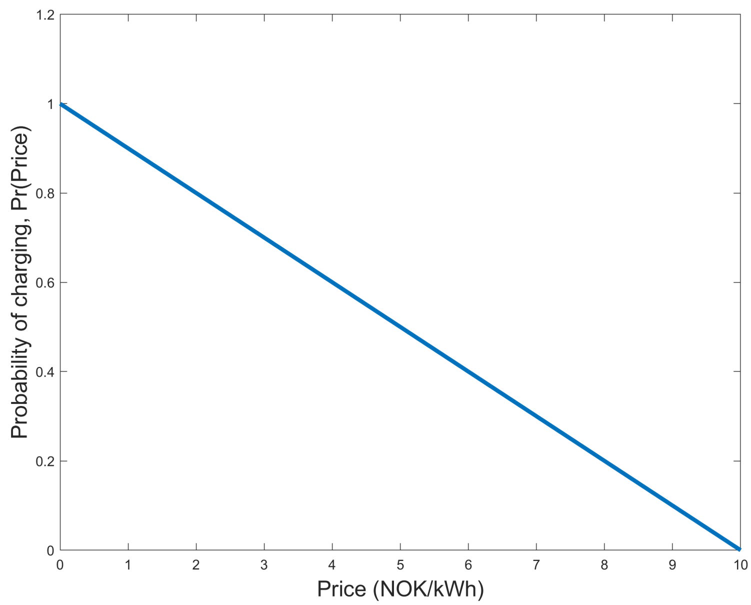


Figure 3.18: Probability of charging in terms of price, for a maximum price of 10 kr/kWh

3. **Distance to the charging station**

The work of Yang et al. [2016] sheds light on the importance of modeling the charging choice as related to the route choice among EV drivers.The fact that EV cruising ranges are shorter than traditional vehicles makes their drivers worry about the battery and strongly influences their charging station and route choices. Therefore, when an EV driver has the need to charge, the charging station attributes such as charging time and location will determine which route to take. Findings show that agents prefer those stations closer to the origin (where the battery level is still close to the initial).

Whereas traditional route choice can be modeled from a number of basic level of service attributes (such as time, fare or road grade), the possibility of charging and the specifics of the stations play a pivotal role in EV route choice (Yang et al. [2016]). Accordingly, drivers will evaluate jointly the level of service of the possible routes and the charging opportunities they offer.

When modeling the choice of a driver among a set of available stations to charge, they will not evaluate their utility by the distance to the stations from their origin or destination, but based on the detour that these stations involve in their route to work or home. The detour can be measured in time, distance, or any other set of attributes that measure the level of service of a route.

A concept already introduced by other authors in public transport route research (Yao et al. [2020], Raveau et al. [2011]) and used again in the work of Yang et al. [2016] is the angular cost of a route, where the level of service (and hence the probability of an agent choosing this route) decreases as the angle formed by the detour increases (see Figure 3.19). In the study at issue, the triangle is always the one formed by the Origin -Charging Station - Destination (henceforth O-CS-D).

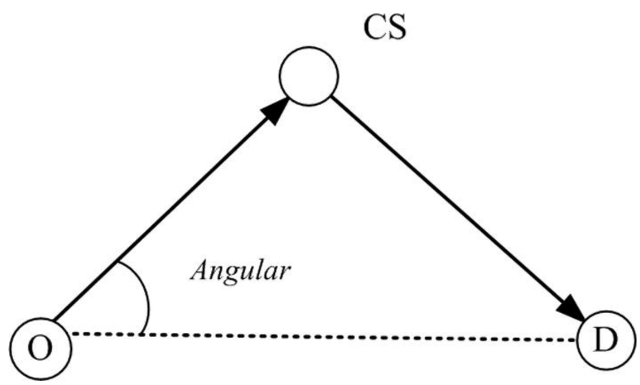


Figure 3.19: Route angular cost. Source: (Yang et al. [2016])

In the model developed in this thesis, the approach is very similar. However, it is not based only on the distance and the angle formed by the three locations, but on the total driving distance. This model can more accurately account for the roads configuration and give a more realistic view of the time and distance used in every charging detour. To this end, we use the OSRM engine (Luxen and Vetter [2011]) to generate 3 routes for each combination of O-CS-D. If an agent has a set of 15 available stations, the model will compute 45 routes in order to assign a probability of charging to each of them. These three routes are O-CS, CS-D and O-D, and the model will evaluate the proportional distance increase in the sum of $(O-CS)+(CS-D)$ with respect to the original route $O-D$.

The range anxiety (as it is commonly described in the literature) has a stronger effect on some agents than others. Those who do not regard depleting their batteries before charging can be more prone to driving longer distances to charge when they need to. Others will preferably choose stations that do not involve a great detour from their original route, and will prioritize the ones closer to their origin. To characterize agents in this range of behavior, the model proposed in this model proposes a randomly-generated factor for each agent.

Studies suggest that agents will consider a maximum detour of 1750 m in trips where the distance is within the range of 10 and 20 km (Sun et al. [2016]). The mean distance of travel per trip varies widely among studies, since different countries have very different urban configurations. For instance, the Norwegian Institute of Transport Economics estimates the daily travel at 3.26 trips per day and a total distance of 47.2 km, which gives a distance of 14.48 km per trip (Hjorthol [2014]).

From this data, it is possible to assume a realistic range where most anxious agents will prefer routes with a detour smaller than 10% and those willing to travel further to charge will consider stations that require up to 60% of added distance to the route.

In a similar fashion of the SOC probability function, the probability of charging is only 1 when the there is no detour to charge in a given station. On the other hand, probability will drop to 0 when the added distance to charge is above the agent's preference of maximum distance. In between these thresholds, this model considers a linear function as illustrated in Figure 3.20.

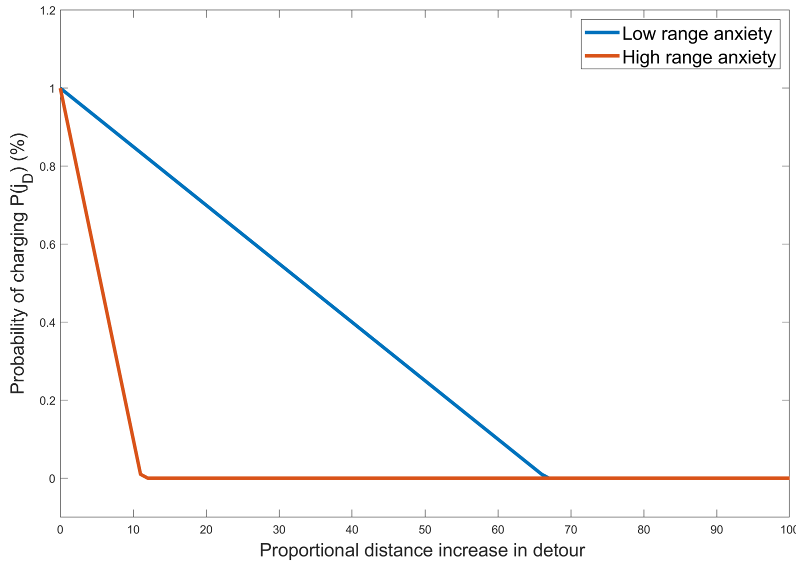


Figure 3.20: Probability of charging in terms of the detour added distance, for agents with low and high range anxiety.

The mathematical formulation of this function is as follows:

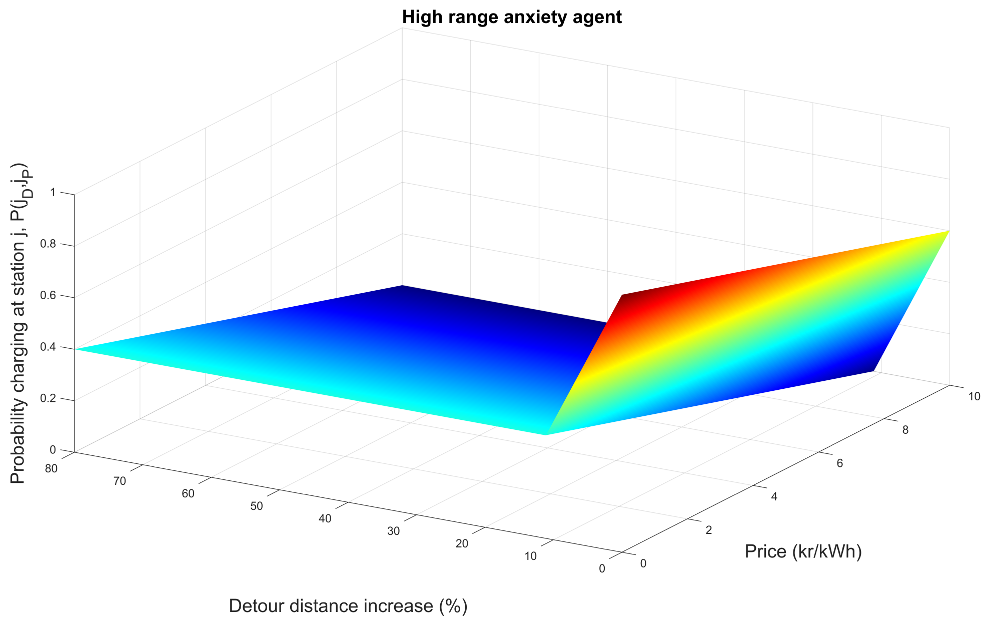
$$P(j_D) = \begin{cases} 1, & \text{if there is no detour} \\ 1 - \frac{Dist_{Station_j} - Dist_{min}}{Dist_{max} - Distmin}, & \text{otherwise} \\ 0, & \text{if detour} \geq Dist_{max}, \end{cases}$$

In this formulation, the minimum distance is equivalent to the original distance between origin and destination (home-work), without the need of including a charging station in the route.

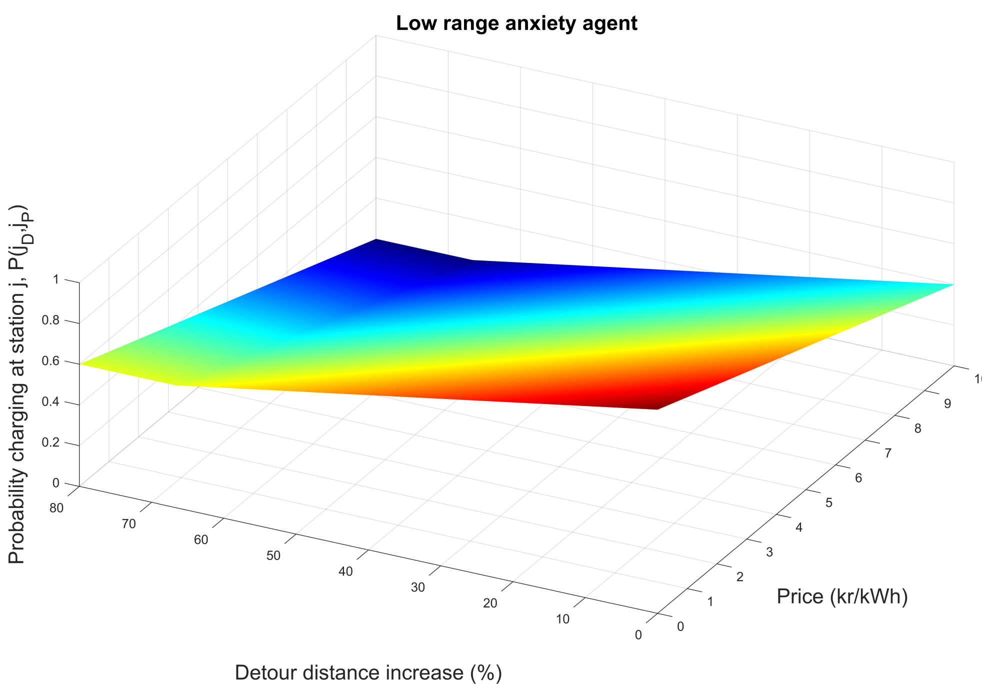
Now that the effect of each variable has been modeled separately, it is possible to analyze how they interact and condition the choices of the agents jointly.

In the overall, the state of charge of the battery will be dominant, as it multiplies the total probability of charging in a specific station. If the SOC of the agent is above the maximum threshold, the total probability of charging will be zero. On the other hand, if the SOC is below the agent's desired minimum threshold, the total probability increases quickly.

First, we can have a look at the station-dependent variables (distance and price). In Figure 3.21, we can appreciate how the probability of charging at a given station decreases with both the price and the detour added distance. Nevertheless, this decrease is not as abrupt for agents with low range anxiety as it is for agents with high range anxiety.



(a)



(b)

Figure 3.21: Probability distribution of charging in terms of the station-related variables. Cases of agents with high and low range anxiety.

We can see how agents with a higher range anxiety are less responsive to price, as they prioritize arriving to the charging station as fast as possible and do not mind paying more for a closer station to their route (see Figure 3.22). In the figures, at a 0% distance increase, the probability of charging at a price of 10 kr/kWh for an agent with high range anxiety drops only to 0.6. In contrast, the agent with a lower range anxiety does not mind driving longer to charge at a lower price, and he is more sensitive to price. The probability drop at 0% distance increase is to 0.4 when the price reaches 10 kr/kWh.

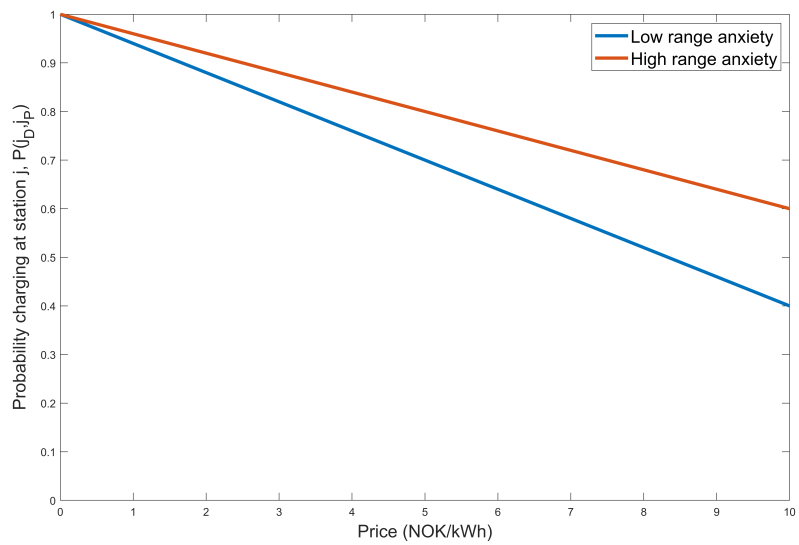
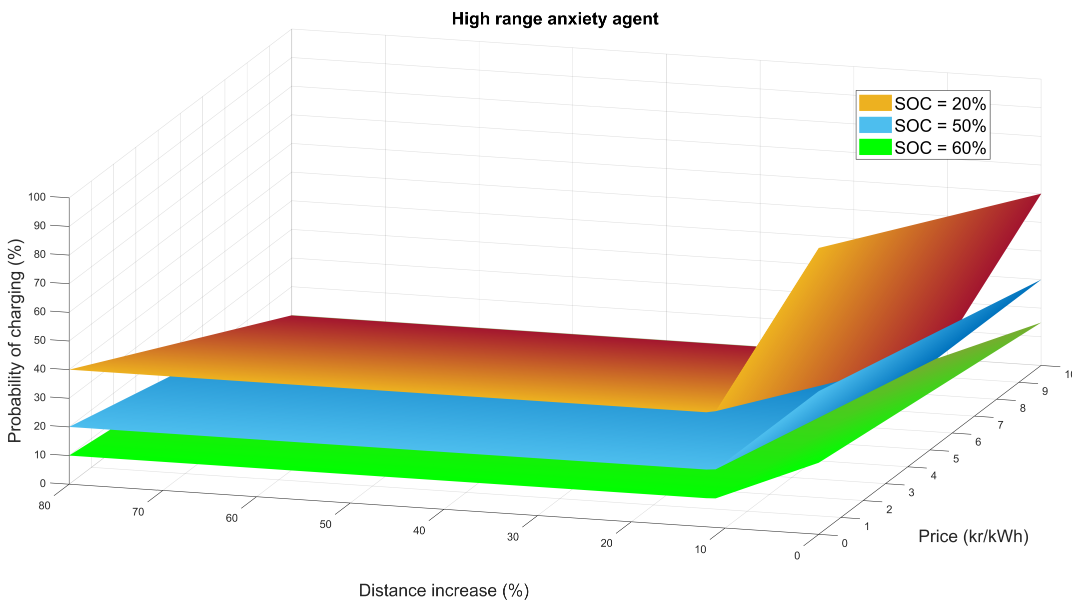
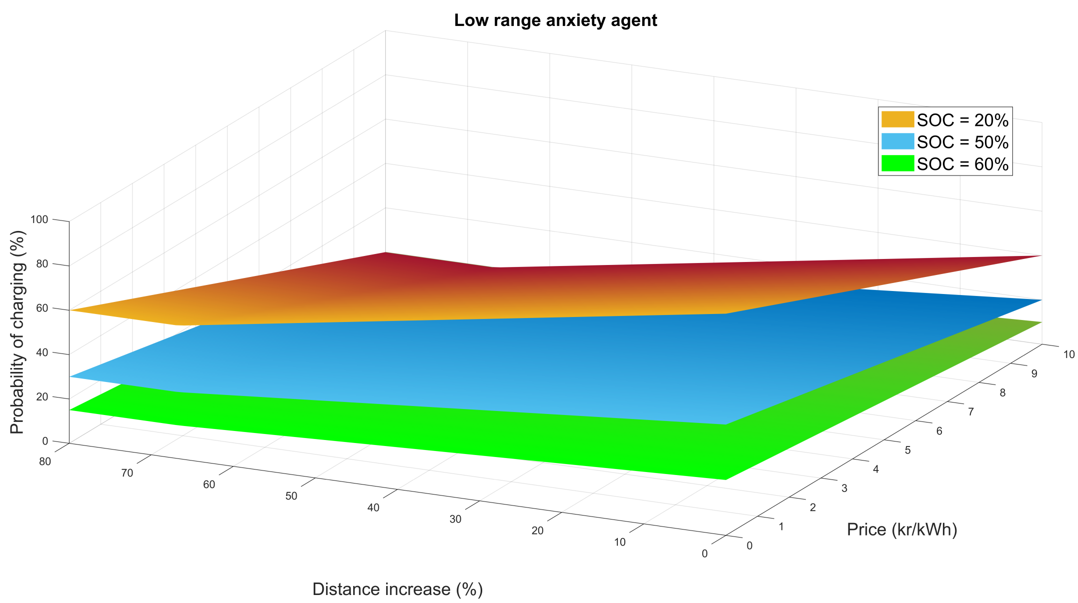


Figure 3.22: Sensitivity to price of agents with high and low range anxiety (at 0% distance increase).

Although these station-dependent variables have a great impact on the probability the agent assigns to each station, the overall probability of charging is mainly determined by the battery state of charge, as indicated before. Figure 3.23 supports this phenomenon, where we can clearly see how the SOC of the agent is the more determinant factor to the probability of charging.



(a)



(b)

Figure 3.23: Probability of charging in terms of 3 different SOC levels, distance and price of the stations.

4 | Cases of implementation

The purpose of this thesis is to study the feasbility and potential benefits of introducing Locational Marginal Pricing (or nodal pricing) as economic signals to control the charging demand of the EV fleet and optimize their operation in the grid. Locally pricing the energy at stations is introduced as a new charging strategy (Local Pricing), and in this section, it is compared to two other more common reference strategies, the uncontrolled scenario, and the centralized control (see section 2.4).

At the same time, these three strategies will be simulated for two different sets of agents. One smaller pre-defined set over a single day, and a larger randomly-generated set over several days.

4.1 Charging Strategies

The behavior of agents has been modelled in section 3.5.2, and in this one, the focus is on the implementation details of the strategies to affect the agents' behavior. An overview of the three strategies is hereby presented:

As mentioned in section 2.4, the central operation scheme for charging implies the bi-directional real-time communication between a centralized control system and the fleet of EVs. In this case of application, the objective function is the minimization of the cost of charging in terms of the price for the grid.

On the contrary, decentralized operation schemes for charging imply that decisions are taken by agents in order to fulfill their own charging goals, and not by the CCU (Ma et al. [2011]). THe price is dynamic (influenced upon) in the decentralized control, but static at the others, and the value is 3.3 kr/kWh as an estimation of Norway's current offer (see 3.5.2.

Table 4.1: Summary of the charging strategies

Strategy	Description	Price at station	Variables influencing the station choice
1. Uncontrolled charging (Dumb)	Agents charge in the station that implies the least detour distance from their original route.	Static 3.3 kr/kWh	Distance (detour) from the agent's path
2. Centrally-controlled charging	The agents are assigned a charging station by the aggregator (CCU): The one with the cheapest price for the grid.	Static 3.3 kr/kWh	Cost of energy for the grid
3. Decentralized controlled charging (Smart pricing: Local Pricing)	The agents choose independently upon their own preferences. The control action is on the price of energy at the stations.	Dynamic	SOC, Distance and Price

4.1.1 Uncontrolled charging

Uncontrolled or dumb charging (Galus [2012]) refers to the scenario where agents charge their vehicle when the need arises, and they simply choose within the closest facilities to its current location. If the agents had the habit to charge either at home or at work, the only variable upon which they make decisions is the SOC of their vehicle after arrival. In our case of study, where agents only charge in fast charging stations located in public facilities, an uncontrolled or dumb scenario would imply that agents recharge their vehicle when the battery is below a minimum desired level of energy, wherever they find themselves at the moment and with no consideration to other factors but the proximity of the stations available. This would be equivalent to the most common behavior among drivers of conventional (ICE) vehicles.

In the model at issue, the agents decide whether they need to charge the vehicle in their way before they leave their current location, that is, if the vehicle has less remaining energy upon arrival than the desired minimum. Once the agent has taken the decision to charge in its way, it will pick the station that fits best its interests and reserves a spot. As mentioned in section 3.5.2, the agents will choose a station upon three factors: their SOC upon arrival, the price of energy, and the detour to reach a station. If the price of energy is static among all stations, and they have already chosen to charge, the stations are indeed assigned a probability that is only dependent on the detour needed to reach them along the path. The probability function of an agent *i* charging at station *j* modelled in equation 3.2, is therefore reduced to:

$$Prob(i, j) = P(j_D) \tag{4.1}$$

After all stations have been assigned a probability, the first will be chosen by the agent and included in the driving path.

The algorithm would be as follows:

Algorithm 1: Dumb charging algorithm

The agent is about to leave its current location;

if $SOC_{arrival} \leq SOC_{min}$ **then**

> *Assign probabilities of charging for all stations available, following the function:*
>
> $Prob(i, j) = P(j_D)$;
>
> *Reserve a spot in the one with the highest probability, which is the closest station (minimum detour);*
>
> *Drive to the chosen station along the route;*
>
> *Charge;*
>
> *Drive to final destination;*

end

This charging strategy marks a reference scenario where agents assign the highest utility to charging since they are only choosing the closest station without regards to the price of energy.

4.1.2 Centrally-controlled charging

As opposite to the dumb charging strategy, we find the centrally-controlled charging operation. Controlled charging involves the option to actively schedule the place and time of recharges. The assignment of stations to agents would be made by a Central Control Unit (CCU), also referred as aggregator. To make decisions, this aggregator must have access to the state of the whole system, involving not only the power grid but also the agents. The optimization of the coordinated system as a whole is only viable when the complete state of the system is known as in this case, which represents its main benefit. However, it requires real-time direct communication between the CCU and all the entities, agents and power grid.

This strategy of charging presents two main drawbacks. Firstly, it involves voluntary participation and lease of data from the agents, who may probably find intrusive to share the state of their vehicle and route plans with an aggregator. Second, all scheduling responsibility lies on the CCU, and with a large number of agents in the system, it may become computationally unfeasible to schedule the charging with a response time low enough.

The objective of centrally-controlled charging is to reduce the total cost of charging (in kr/kWh) from the perspective of the power grid. Different stations will have different nodal prices, due to congestion and transmission losses in the grid (see section 2.5.2), and the CCU will therefore assign the agent where the energy is cheapest (lowest nodal price). This is an optimization in space but not in time, as the CCU is assigning the cheapest station at a given moment but the price of energy from the grid might be high then.

If it were to be computed in retrospect, such as at the end of a day, the scheduling could be optimized not only in space but also in time. The aggregator would be able to assign agents to stations at the time of day when they would cost the least. Nevertheless, this is not possible in an scenario where the scheduling is done upon request of the agents (real-time response). This strategy may therefore imply that agents have to deviate or travel further in order to charge, and their utility of charging decreases as a consequence of their preferences not being respected.

The algorithm of centrally-controlled strategy is:

Algorithm 2: Centrally-controlled charging algorithm

The agent is about to leave its current location;

if *SOC (v,t)* $< SOC_{mindesired}$ **then**

The CCU computes the price of energy at every station of the set;

The agent is informed of the station to use along its way;

The agent drives to the station first;

Charge;

Drive to final destination;

end

4.1.3 Decentralized controlled charging: Local Pricing

As mentioned before, the main benefit of decentral strategies is the lack of needing constant communication between stakeholders. Responsibility no longer lies on the aggregator but on each of the agents involved when they make their own decisions towards their goals of charging. It is computationally more simple, and less intrusive with the agents' data.

The difference between this controlled strategy and the uncontrolled strategy is the actuation on one of the parameters that has influence on the agents' behavior: the price of charging. The price is no longer static, but by changing it will influence the decisions of agents on whether to charge and where.

We account on the agents' behavioral parameters to determine the fitness of a situation for their goal of charging (SOC, distance and price). Before an agent leaves its current location (home or work), if the SOC upon arrival is less than the desired minimum, it will check the status of the stations with open charging points. From the information on these stations, the agent will decide whether or not to charge, and will choose the station that best fulfills its preferences.

To quantify the fitness of each station to the agent's goals, it is modelled by the probability function previously defined in equation 3.3, hereby reminded:

$$P(i,j) = P(i_{SOC}) \cdot (P(j_D) \cdot x_D + P(j_P r) \cdot x_{Pr}),\ i = 1,...,n,\ j = 1,...,m \tag{4.2}$$

After the agent has checked prices and distances on all stations, and has assigned them a probability of charging following this function, it will only charge if the one with the highest probability is fit enough. For instance, if all stations have very high prices, or if the only available ones are far away, the agent might decide not to charge at this moment. In order to model this decision, we will generate a random number between 0 and 1 that will in a certain way represent the agent's level of exigency to charge at the moment, LE_i. If the level of exigence is high, for instance $LE_i = 0.9$, very few stations or none will be over this level of probability (taken from function 3.2). On the contrary, if the level of exigence is low, for example $LE_i = 0.2$, a good part of the stations will be over this level of probability and the charging event will most probably happen.

Therefore, formally expressed, an agent i will only charge among a set of m stations if:

$$max(P(i,j)) > LE_i,\ j = 1,...,m \tag{4.3}$$

The algorithm for an agent is as follows:

Algorithm 3: Decentral charging algorithm

The agent is about to leave its current location;

if $SOC_{arrival}) < SOC_{min}$ **then**

The agent is assigned a charging level of exigence, which is a random number between 0 and 1 (LE_i);

Check the stations available;

for i = *1:* n **do**

The agent assigns a probability of using a charging station to each available station in the set;

$P(i,j) = P(i_{SOC}) \cdot (P(j_D) \cdot x_D + P(j_P r) \cdot x_{Pr}),\ i = 1,...,n,\ j = 1,...,m$, *see equations 3.3*

end

if *max(Prob(Agent*$_i$*,* $Station_j) \geq LE_{Agent_i} for\, j = 1,...,nstations$ **then**

The agent chooses the station with the highest probability of charging;

The agent includes the station in its route;

The agent drives to the station first;

Charge;

end

Drive to final destination;

end

In this strategy, the main advantage of this strategy is the possibility of influencing the agents' choices by changing the parameters to which they are sensible without the need of knowing the complete state of the system. In this simplified model of agents' behavior, we will act on the price of charging at the stations to regulate and optimize operation, but acting on other parameters could be studied (parking, pricing over time, etc.).

In order to make the actuation on the price effective in terms of agents' behavioral shift, the clearing of the price is key to this charging strategy.

Clearing the local price of energy at the stations

The price of energy at different charging stations is becoming more dependent on the place and time of charging. Price of energy from the transmission grid is already more volatile over time than before, due to the introduction of renewable energies (for which the generation varies along the day). That is why we see very strong fluctuations in the price of energy in zones with a high dependence on wind power like DK2 (see Figure 3.3). Moreover, the price of energy is also becoming more volatile at a given time and among different places in the distribution grid. With the introduction of DER and energy storage at a local level, the price difference between stations will become more significant, added to the already existing cost of transmission losses and congestion (Frontier Economics [2009]).

Nordic countries belong to the Nordpool Market (Nordpool, 2020) where the price of energy is cleared by zone (bidding areas) and it is constant within this geographical extension (see section on Zonal Pricing, 2.5.2). Trondheim and Steinkjer both belong to the NO3 zone (see Figure 4.1), and the price of energy is therefore the same within this whole area.

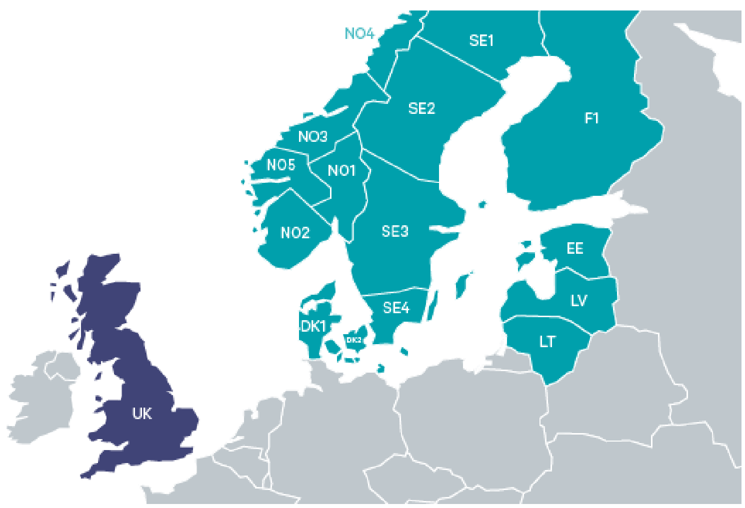


Figure 4.1: Bidding areas within the Nordpool Market (Nordpool, 2020)

Nevertheless, other countries have started pricing energy according to its real cost at each bus of the system (nodal price, Holmberg and Lazarczyk [2012b]). In nodal pricing schemes, the price paid for energy differs from one bus to the other. If we look at the equation defining Locational Marginal Pricing, at a given time (for which the system cost of energy is the same in the whole area), different nodes will have different costs of energy depending on transmission and losses:

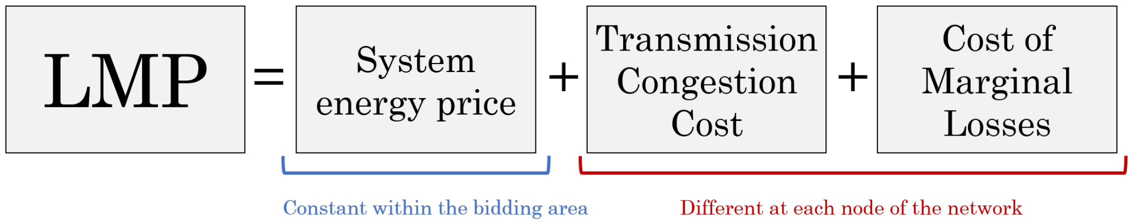


Figure 4.2: LMP components defining the difference between nodal prices at a given time.

We can take the distribution grid at issue to illustrate these differences in prices among the buses at a given time. To do so, we run the ACOPF problem in the grid at a moment of high consumption, for instance 8:00 AM, February 3rd, 2012 (for which we have data as the day with the highest consumption of the year). At this time, the energy price given by Nordpool Market (considered as generation price in this problem) was 400.13 kr/kWh (see section 3.3). The price of energy (kr/kWh) in the buses where the charging stations are located are gathered for two cases of usage:

- First, we only include the consumption of households at this time, for which we have historical record of the power demand.

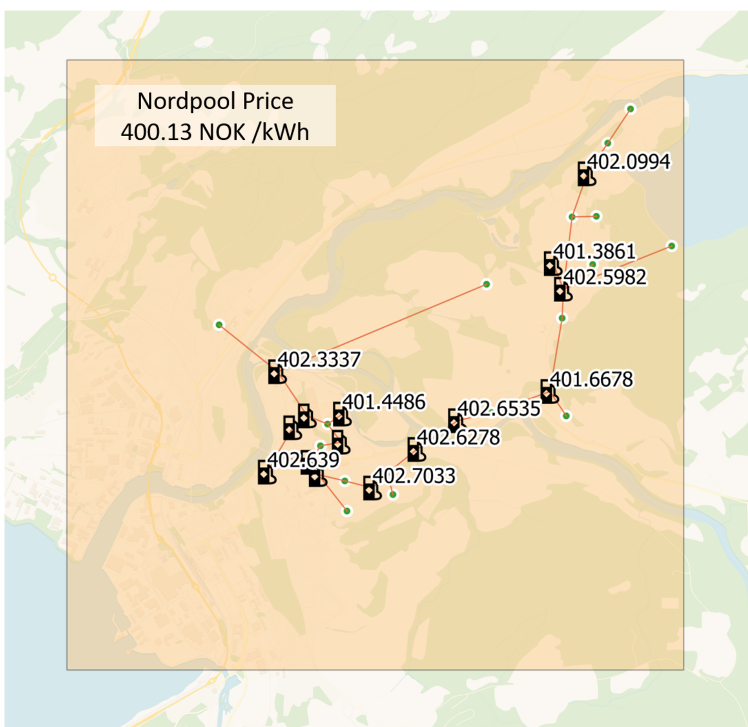


Figure 4.3: Nodal prices of energy at the buses of the charging stations, when no cars at connected in kr/kWh

- Second, adding the consumption of 2 cars charging at 150 kW in every station.

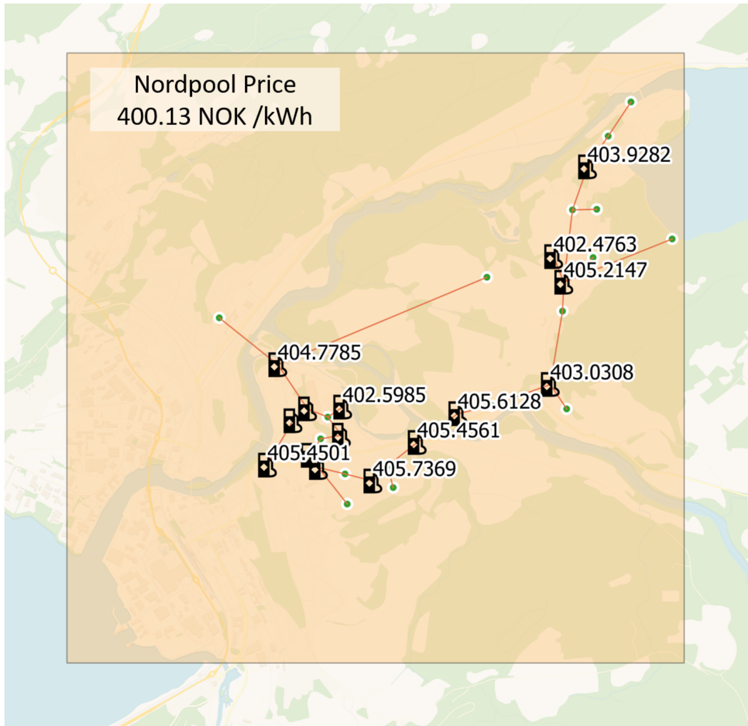


Figure 4.4: Nodal prices of energy at the buses of the charging stations, when 2 cars are connected at each station and charging at 150 kW, in kr/kWh

From the two previous Figures 4.3 and 4.4, we can see how the nodal price of energy at the buses of the charging stations differ from the energy price given by the Nordpool Market. The prices increase in a maximum of 0.6% in the first case, and 1.4% in the second. After observating simulations at different hours of the day, 1.5% has been found to be the highest price difference between nodal prices and the system (Nordpool) price (generation price in the ACOPF model).

In this model, where there is no local production of energy or storage, and where both generators (transmission grid and hydroelectrical power plant) take the Nordpool price, the differences in nodal prices are only due to congestion and transmission losses (Frontier Economics [2009]). In a resilient electrical grid as this one, the differences are very small, and for that reason there is the need to design a pricing scheme where the differences are felt by the agents.

With the intention of making this model mock the scenario where nodal price differences are bigger, these proportional increases in the price will be magnified. If we want the agents to be equally sensitive to both the price given by the system (Nordpool) at a given time, but also to the difference in price among the local stations, we can divide the price range in two equally contributing parts. If the maximum price the agents will be charged for energy is 10 kr/kWh (see section 3.5.2), each part can contribute up to 5 kr/kWh:

- The first 50% of the price will be given by the Nordpool price of energy at a given moment, with respect to its maximum achievable value. Within the dates considered, the maximum price of energy in zone DK2 of the Nordpool Market is 403.3 kr/kWh (see Figure 3.3), and this is established as the maximum of a linear price function ranging from 0 to 5 kr/kWh:

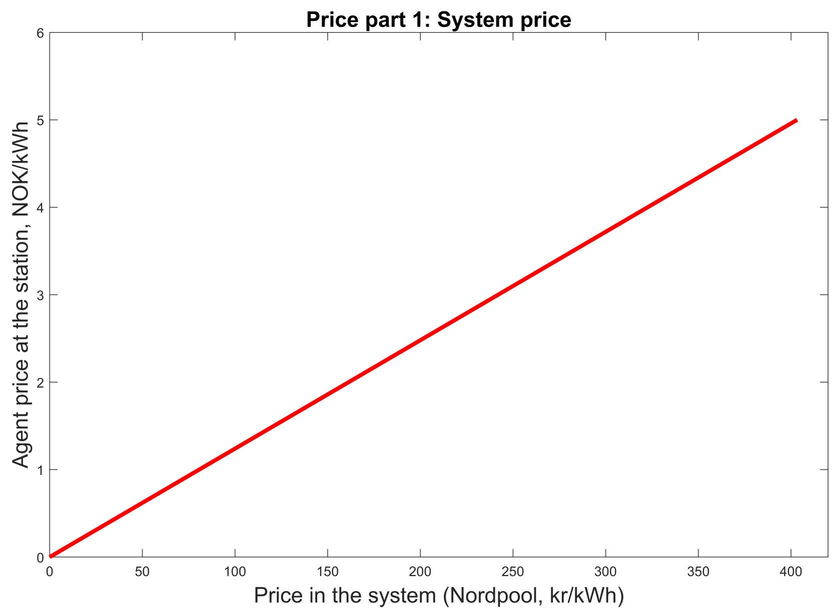


Figure 4.5: First part of the price: Linear function of the Nordpool price of energy at a given time.

- The second 50% of the price will be determined by the proportional increase in the nodal price with respect to the Nordpool price, due to congestion and transmission losses. We define the nodal price difference as the proportional increase between the system price and the nodal price, due to congestion and losses. Taken 1,5% as the maximum price increase between these two magnitudes, again we define a linear price function ranging from 0 to 5 kr/kWh:

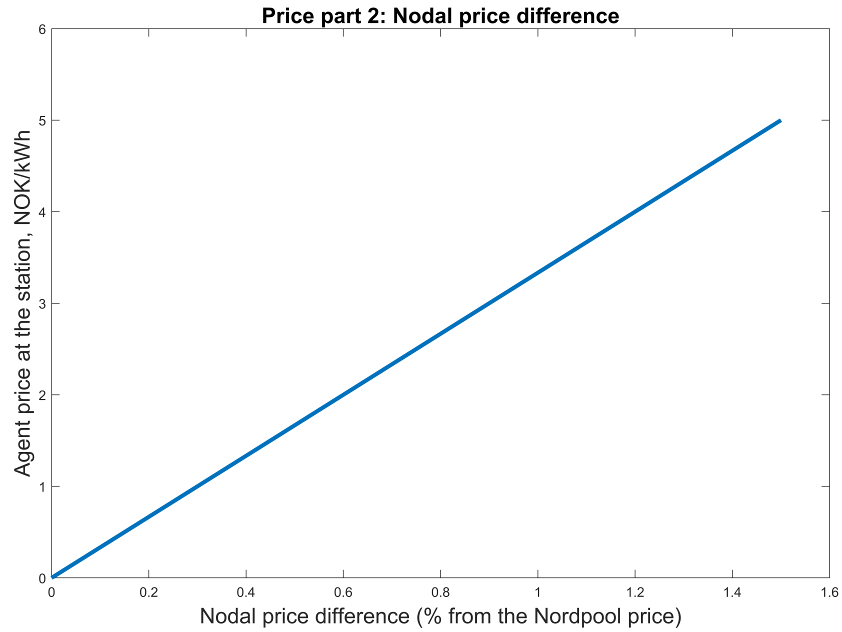


Figure 4.6: Second part of the price: Linear function of the nodal price.

Putting these two contributions to the price together, we get a range of 0 to 10 kr/kWh for the price the agents will pay at the charging station. In Figure 4.7, we can appreciate the contribution of the Nordpool price in the red line to the total price ranging from 0 to 10 kr/kWh. In the blue stripe, there is the contribution to price from nodal price differences, at each possible Nordpool price.

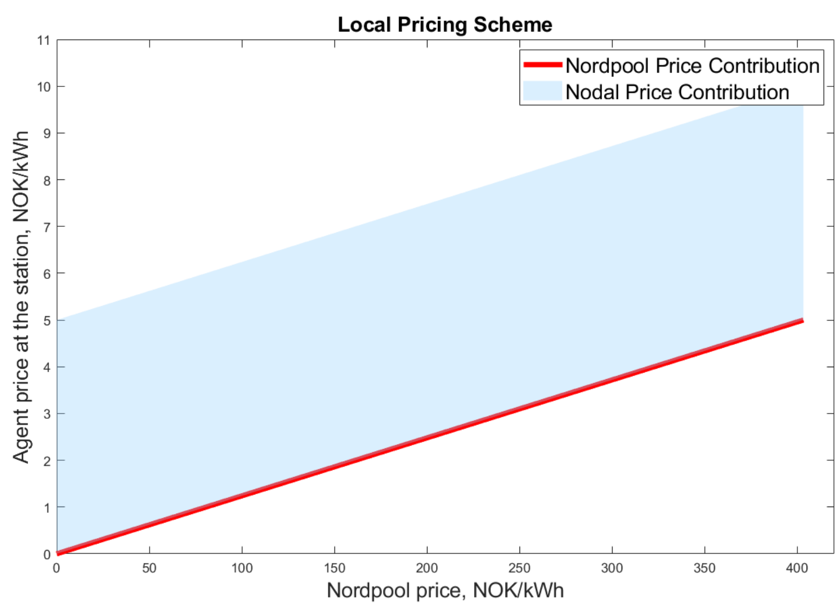


Figure 4.7: Local pricing scheme based on both Nordpool and nodal prices of energy.

In order to clarify Figure 4.7, we can represent the axis of nodal price difference (%) and three illustrative points where the price is calculated:

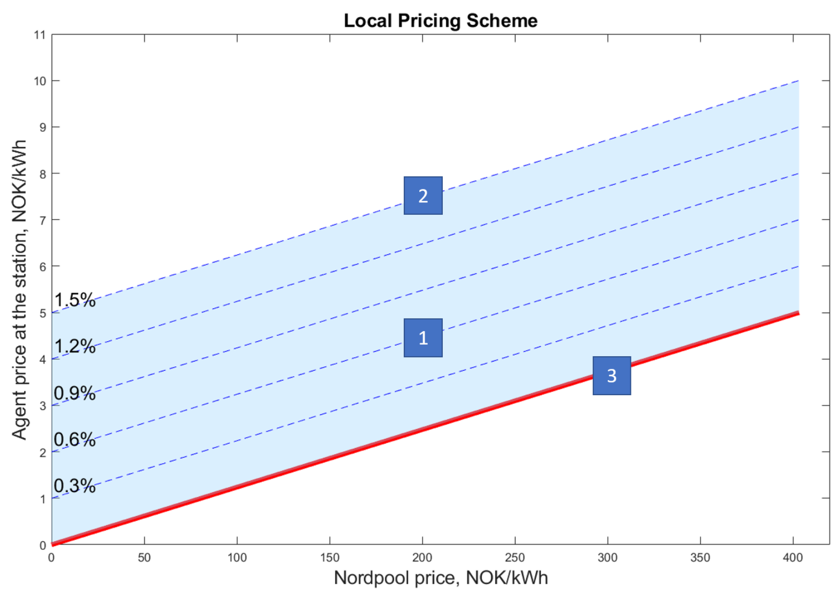


Figure 4.8: Second part of the price: Linear function of the nodal price difference: Explanation aid.

Point	1	2	3
Nordpool Price (kr/MWh)	200	200	300
Nordpool Price contribution (kr/kWh)	2.5	2.5	3.75
Nodal price difference (%)	0.6	1.5	0
Nodal Price contribution (kr/kWh)	2	5	0
Total price at the station (kr/kWh)	4.5	7.5	3.75

Table 4.2: Price calculation for points in Figure 4.8

4.2 Simulation scenarios

We will now define the simulation scenarios that will be used to analyze and discuss the feasibility and benefits of the proposed charging strategy.

If the set of agents is generated in a way that random characteristics are assigned to each one of them (Monte Carlo simulation method, see section 2.5.2, comparing charging strategies will need the simulation of large sets of agents and for long time, in order to avoid very distant scenarios in terms of energy demand. Each time an agent is generated, and each time an agent faces the decision of whether or not to charge, random numbers are assigned in order to simulate their behavior. By the law of large numbers (LLN), when repeating this random roll a greater number of times, we will generate a sample of agents whose characteristics' mean approaches the expected value. On the contrary, if few agents are simulated, or if the time of simulation is short, randomness might incur in deviant sets of agents, and therefore different demand scenarios.

To overcome this problem, the first case of implementation will be using a fixed set of agents for which the energy demand is known. The second and more illustrative case of implementation will simulate a randomly-generated larger set of agents over several days. A summary of the simulations can be appreciated in Table 4.3.

Table 4.3: Simulation scenarios

	Charging Strategy		
Set of Agents	Uncontrolled	Centrally-controlled	Decentrally-controlled (LMP)
Small fixed set, 20 agents	Simulation 1	Simulation 2	Simulation 3
Large randomly-generated set, 100 agents	Simulation 4	Simulation 5	Simulation 6

Therefore, the first is to establish a number of agents to simulate. The set has to be large enough to pursue an equal distribution of the agents' characteristics among simulations, but it can't be too large to manage computationally. Simulations in this thesis are run on a computer with an Intel Core i7-7500U CPU processor at 2.70 GHz, running Microsoft Windows 10 Home. With this computing power, the simulation of 100 agents over 1 day, takes about 15 minutes to complete. It is important to consider that most of the time is used in synchronously running the Matlab® Engine from the JAVA simulation of the agents, and from the Map server providing routes in real paths (OSMR, Luxen and Vetter [2011]). However, the only way to avoid this consumption of computing time would be by not using the MATPOWER package on Matlab® and implementing the ACOPF problem in JAVA, which is not the scope of this thesis. Considering this computational speed, if we want to simulate several days, for instance 15, sets of more than 100 agents would take too long to simulate. Proof is given for the fact that 100 agents is enough to overcome deviation of their characteristics in section 4.2.2.

Then, if we are going to start by simulating a fixed set over a day, it is important to estimate the number of cars charging in a single day. If the agents are assigned either one of the three most common EV models (see Table 3.4), around one third of the population will own the same model. The charging frequency of the models considered are given in Table 3.6, and therefore the probability of an agent charging at a given day is:

Table 4.4: Probability of charging in a given day for each EV model.

EV Model	Charge duration [days]	Probability of charging in a given day
Nissan Leaf	5	1/5
Tesla S	12	1/12
Volkswagen e-Golf	4	1/4

If the total set of agents has a size of 100, and the three EV models are equally present, the number of cars charging in one day is given by Equation 4.4.

$$N_{cars,1day}(N_{agents}) = N \cdot \frac{1}{n_{models}} \cdot \sum_{model1}^{n_{models}} Prob_{charging}(model) \tag{4.4}$$

$$N_{cars,1day}(N_{agents}) = N \cdot \frac{1}{3} \cdot \left(\frac{1}{5} + \frac{1}{12} + \frac{1}{4}\right)$$

$$N_{cars,1day}(100\, agents) = 100 \cdot \frac{1}{3} \cdot \left(\frac{1}{5} + \frac{1}{12} + \frac{1}{4}\right) = 17.6\, agents$$

This means that in a single day, 17.6 agents will demand charging on average, when their SOC drops below the desired minimum (SOC_{min}).

4.2.1 Reduced fixed set of agents

In this first case of implementation, the set of agents is fixed and so are all their attributes and energy demand. The purpose of this case is to study the short-term energy cost reduction induced by the Local Pricing strategy based on economic signals to agents. This strategy intends to optimize operation in both the short and the long terms, by relocating demand where and when the energy is cheaper. By means of studying this case, we will only see the effect on the first dimension, since the energy demand is given for the day and the only possible cost reduction is by avoiding congested stations where the nodal prices are higher.

If we are going to simulate for a given day, for which the energy demand is known, the number of agents has to be consistent with the number of agents that normally charge in a day. Equation 4.4 gives that, for a set of 100 agents, around 17.6 will charge in a day. For simplicity, we will simulate a set of 20 agents, all of them starting the day with a SOC of 15%, which will induce all of them to charge. The details of their energy demand is gathered in Table 4.5:

Table 4.5: Properties of the 20 simulated agents: energy demand overview

Agent	EV model	$SOC_0[kWh]$	Capacity [kWh]	$SOC_{min}[kWh]$	Demand [kWh]
1	Tesla S	15	100	24	85
2	Tesla S	15	100	51	85
3	Tesla S	15	100	1	85
4	Volkswagen e-Golf	5.37	35.8	19	30.43
5	Volkswagen e-Golf	5.37	35.8	8	30.43
6	Volkswagen e-Golf	5.37	35.8	5	30.43
7	Nissan Leaf	6	40	12	34
8	Nissan Leaf	6	40	22	34
9	Tesla S	15	100	56	85
10	Volkswagen e-Golf	5.37	35.8	14	30.43
11	Nissan Leaf	6	40	9	34
12	Tesla S	15	100	78	85
13	Nissan Leaf	6	40	19	34
14	Nissan Leaf	6	40	23	34
15	Nissan Leaf	6	40	17	34
16	Nissan Leaf	6	40	7	34
17	Nissan Leaf	6	40	23	34
18	Nissan Leaf	6	40	24	34
19	Nissan Leaf	6	40	9	34
20	Tesla S	15	100	22	85
Total energy demand					971.72

The other attributes of the agents are also fixed, namely their home location, work location, home-work route and working times schedule. As these details are less relevant for the energetic study at issue, they are spared, and the geographical locations are summarized in Figure 4.9. In this figure we can see, in red, the home locations of all agents within residential area (shaded red). With a map pin, their work locations within working areas (shaded green). Both home and work locations are linked with dashed lines.

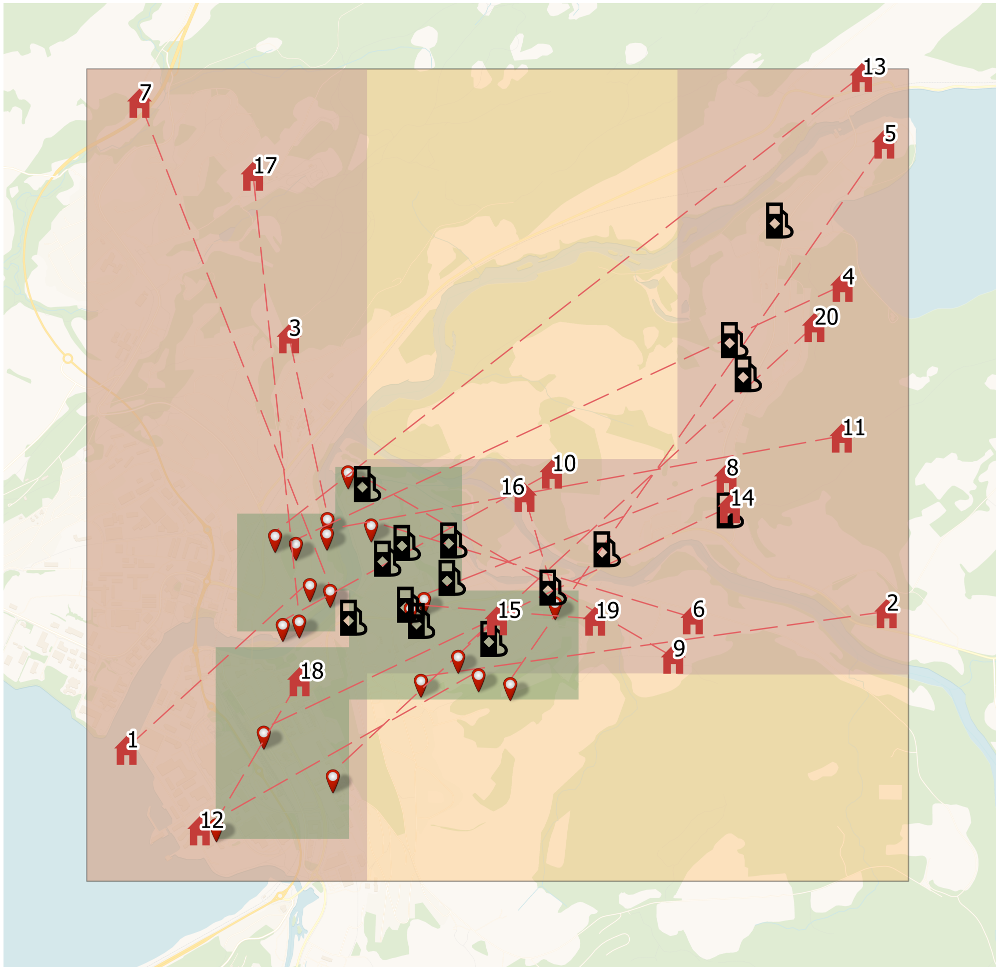


Figure 4.9: Location of 20 agents' home and work locations, together with the set of charging stations in the city

Over the morning of the simulated day, all 20 agents will choose (or be assigned) a charging station in which they will make a stop on their way to work and charge their EVs. The different charging strategies will induce different decisions among agents, as we will see in the results.

4.2.2 Large randomly-generated set of agents

In this second case of implementation, the complete set of agents (proposed size of 100) will be simulated over several days. Simulation over a longer period of time allows the study of the demand optimization over time and not only space: agents can delay or bring their charging forward, according to the energy generation and its price at the moment. Therefore, the demand per day will be determined by the price of energy, and will not be constant as in the previous case.

When the set of agent is large enough, different random rolls of their characteristics will give an average that stabilizes and defines the group. This eliminates the need of defining the group beforehand as in the previous case. For that reason, a different set of agents will be generated for each simulation (one simulation runs for every charging strategy). In order to verify that 100 agents is enough to avoid deviations from the expected values of their features (Law of Large Numbers, LLN), a comparison is hereby presented between the three sets of agents generated for the three charging strategies proposed.

Monte Carlo minimal sample size

The purpose of this brief section is to verify whether a set of 100 randomly-generated agents can properly represent the group, without major deviations of their features from the expected values.

Agents are defined upon several features (attributes), among which, the the study of the agents' behavior, we highlight (see Figure 3.13 and Table 3.3):

Table 4.6: Agent features of relevance for the energetic study.

Agent parameter	Possible Values (Domain)	Probability Distribution	Expected Value
Minimum desired SOC (SOC_{min})	$SOC_{min} \in [0.3, 0.6]$	$SOC_{min} \sim \mathcal{U}(0.3, 0.6)$	$E[SOC_{min}] = 0.45$
Price relevance x_{Pr}	$x_{Pr} \in [0, 0.6]$	$x_{Pr} \sim \mathcal{U}(0.3, 0.6)$	$E[x_{Pr}] = 0.3$
Distance relevance x_D	$x_D \in [0.4, 1]$	$x_D \sim \mathcal{U}(0.4, 0.1)$	$E[x_{Pr}] = 0.7$

The relationship between the sample size and the precision level for the Monte Carlo simulation method used here, is given in equation 2.9. For a 95% level of confidence, the precision level given by a 100 agents sample is:

Table 4.7: Agent features of relevance for the energetic study.

Agent parameter	Probability Distribution	Mean and standard deviation	Level of precision
Minimum desired SOC (SOC_{min})	$SOC_{min} \sim \mathscr{U}(0.3, 0.6)$	$\mu = E[SOC_{min}] = 0.45$ $\sigma = \sqrt{\frac{(0.6-0.3)^2}{12}} = 0.087$	$\Phi = 0.017$
x_{Pr}	$x_{Pr} \sim \mathscr{U}(0.3, 0.6)$	$\mu = E[x_{Pr}] = 0.3$ $\sigma = 0.03$	$\Phi = 0.006$
x_D	$x_D \sim \mathscr{U}(0.4, 0.1)$	$\mu = E[x_D] = 0.7$ $\sigma = 0.03$	$\Phi = 0.006$

The level of precision of these sets are between 1% and 5% for the intervals given, which is more than sufficient to conclude that our simulated sets will accurately have (in average) the features we have modelled.

In order to study the three proposed charging strategies, three simulations will be run with a randomly-generated set of 100 agents each (simulation scenarios 4-6, see table 4.3). We have gathered the agents' properties cited in Table 4.6 over these three sets, to illustrate that average properties of agents correspond to the expected values, as we have calculated in table 4.7.

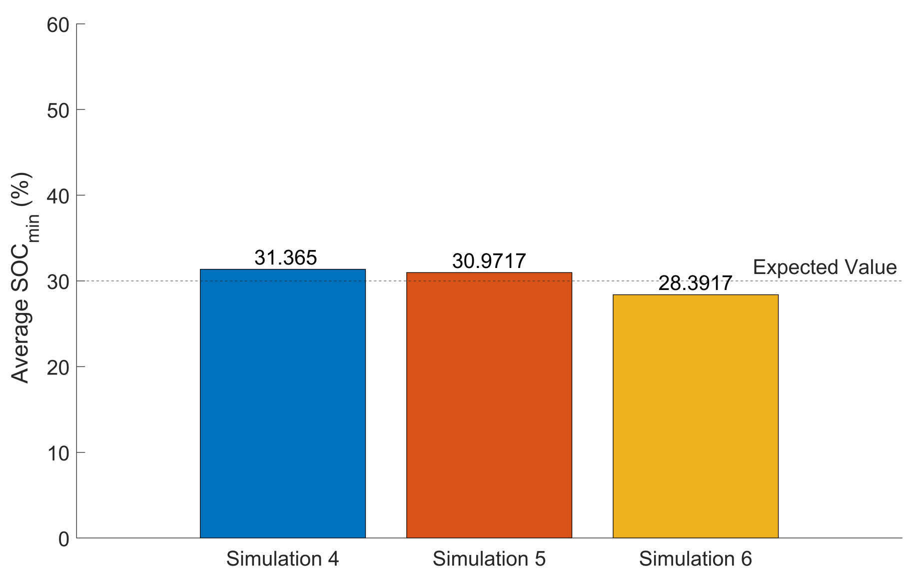


Figure 4.10: Average SOC_{min} in Simulation cases 4,5 and 6.

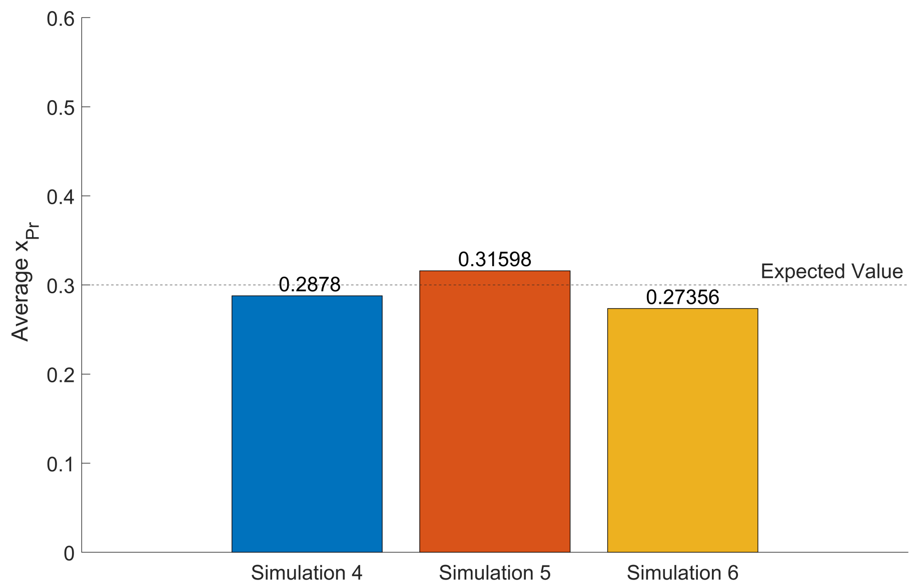


Figure 4.11: Average price relevance x_{Pr} in Simulation cases 4,5 and 6.

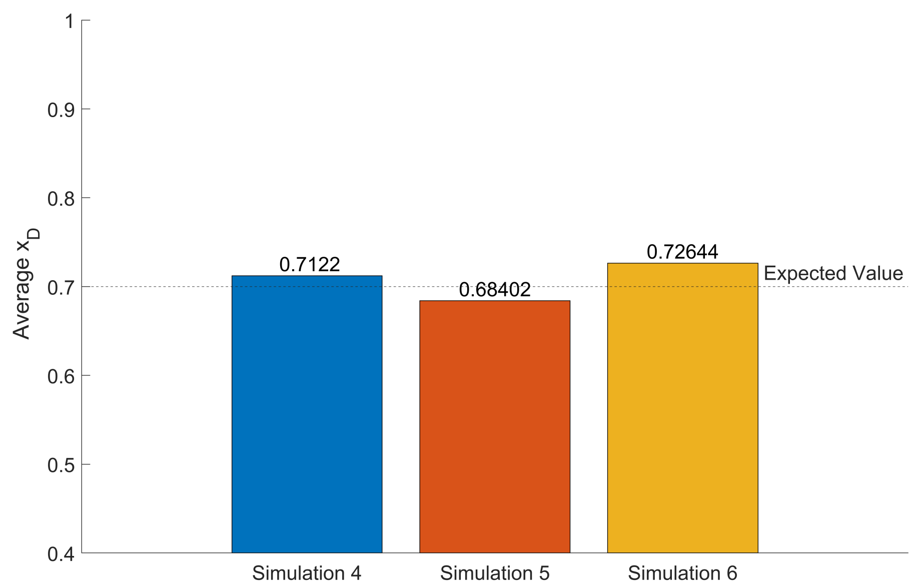


Figure 4.12: Average distance relevance x_D in Simulation cases 4,5 and 6.

We can also calculate the minimum size of the set for the average value of the set to tend to the expected value. In other words, what is the minimum size of the Monte Carlo randomly-generated set if we want to produce a representative one. With the aim of illustrating this, we take the Simulation 5 (Centrally-controlled) as example in Figures 4.13, 4.14 and 4.15.

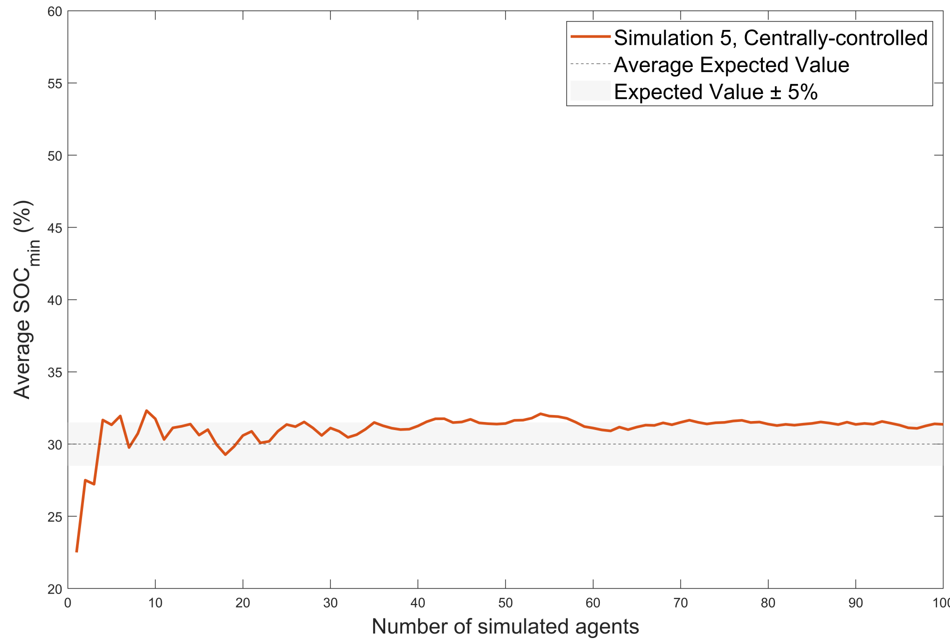


Figure 4.13: Average SOC_{min} in Simulation cases 4,5 and 6.

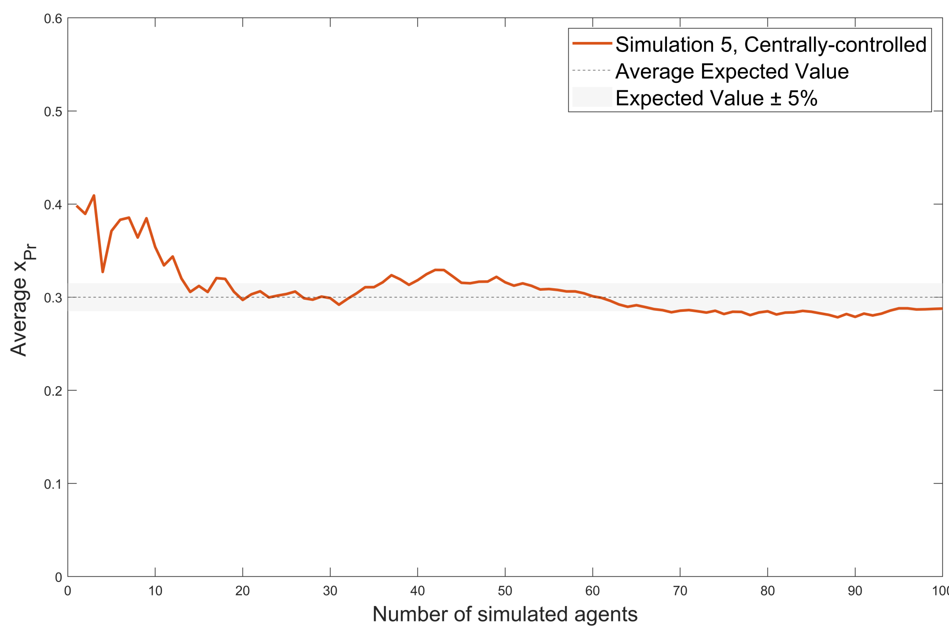


Figure 4.14: Average price relevance x_{Pr} in Simulation cases 4,5 and 6.

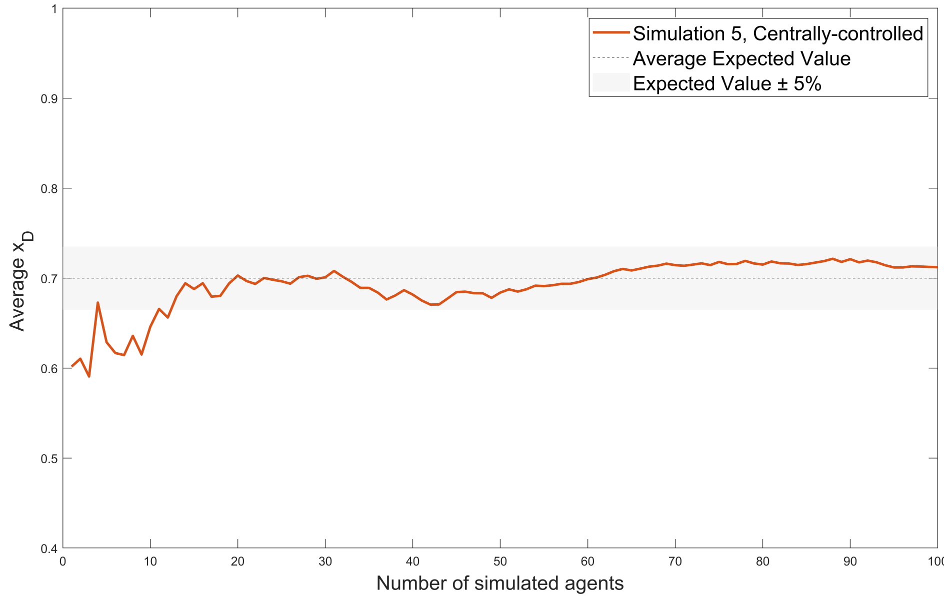


Figure 4.15: Average distance relevance x_D in Simulation cases 4,5 and 6.

We can see that after a maximum of 60 agents (x_{Pr}), the average of the set features are within a 5% range of the expected value. Therefore, we can conclude that more than 60 agents, and in this case 100, can accurately represent the features of the set even though they are generated randomly (see section on the Monte Carlo method, 4.2.2).

5 | Results and Analysis

In this section, the results of all simulations will be presented and accompanied by a discussion (see Table 4.3). For the sake of cohesion, they will be divided in two. First, we will present the results of simulations run with the small fixed set of agents (Simulations 1 to 3) over one single day. Then, a more comprehensive analysis will be given for simulations using the randomly-generated set of 100 agents over several days (Simulations 4 to 6).The purpose is to study separately the effects of decentrally-controlled charging strategy of Local Pricing.

5.1 Comparative study of the cost of energy

With the first group of simulations, the goal is to study its effect on the energy cost at a given time and demand. In other words, relocating the demand in the stations where energy is cheaper to obtain (lower nodal prices). In the second group of simulations, by using the larger set of agents over several days, we study the potential of relocating demand in time, when energy is cheaper to generate and the market price is therefore lower.

5.1.1 Small fixed set of 20 agents. Simulations 1 to 3.

In order to present the differences in cost of energy for the three proposed charging strategies, we can start by summarizing the results in table that will be analyzed hereafter.

Table 5.1: Results summary for simulation scenarios 1-3.

	Charging Strategy		
	Decentralized uncontrolled	Centrally-controlled	Decentrally-controlled (LP)
Total energy consumption [kWh]	971.72	971.72	971.72
Average cost of energy for the grid (nodal price) [kr/MWh]	146.01	145.85	145.87
Average cost for the agent [kr/kWh]	3.3	3.3	6.19

In Table 5.1 we can see how the local pricing strategy can be a trade-off between the centrally-controlled and the totally uncontrolled scenarios, in terms of costs of energy for the grid. By definition of the centrally-controlled strategy, the aggregator always assigns to the agent the station with the lowest nodal price (lowest cost for the grid). Therefore, it is consistent that it has the lowest average price of energy of all three strategies. On the other hand, in the uncontrolled decentralized scenario, agents are the ones to decide where to charge. Given that the price is static for all stations in the uncontrolled scenario, agents will only choose a station over convenience and not the price of energy (see section 4). Under these conditions, agents will choose the closest station to their path, most of the times within the city center and where the congestion of the lines can be higher. That is why this strategy has the highest price of energy of all.

Finally, we have the local pricing scheme, where the nodal price of energy (cost for the grid) is reflected on the price the agents pay for the charging energy (see section 4.1.3), and they are therefore sensible to over-cost due to congestion and losses. The mean price of energy is closer to the minimum (defined by the centrally-controlled strategy), and the slight increase is due to some agents who decide to pay a bit more for a closer station (this small price increase reflects the congestion and losses cost of the nodal price).

If we refer to the price of energy for the agents, it is significantly higher than the cases where the price is constant (first two strategies). We should start by considering the market price of energy for the given day (February 8th, 2020). The price of energy for the morning of this day is $145.89\frac{kr}{MWh}$ in the DK2 zone of the Nordpool Market (AS [a]). Therefore, the price of energy for the agents will range from $1.82\frac{kr}{kWh}$ in the stations with 0% congestion and losses, to $6.82\frac{kr}{kWh}$ in the stations where congestion and losses have an effect on the nodal price. We can see in Figure 5.1 how most of the agents paid over $4\frac{kr}{kWh}$, due to the costs of congestion and losses in the lines where the stations are connected.

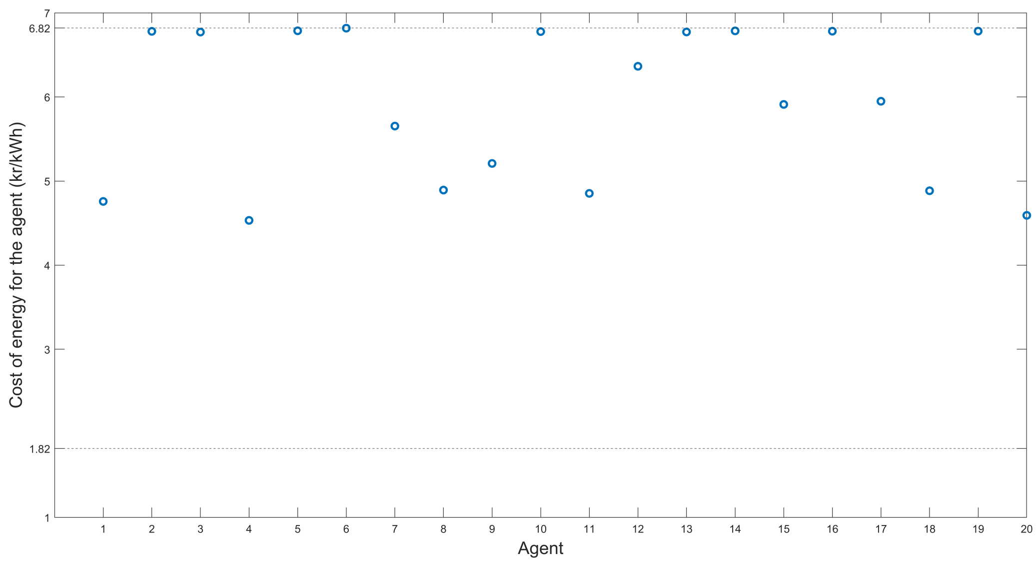
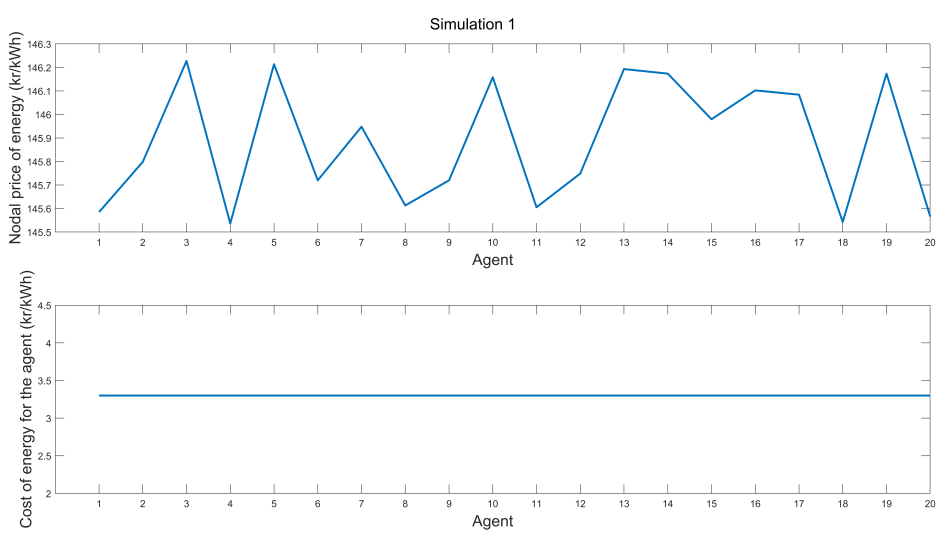
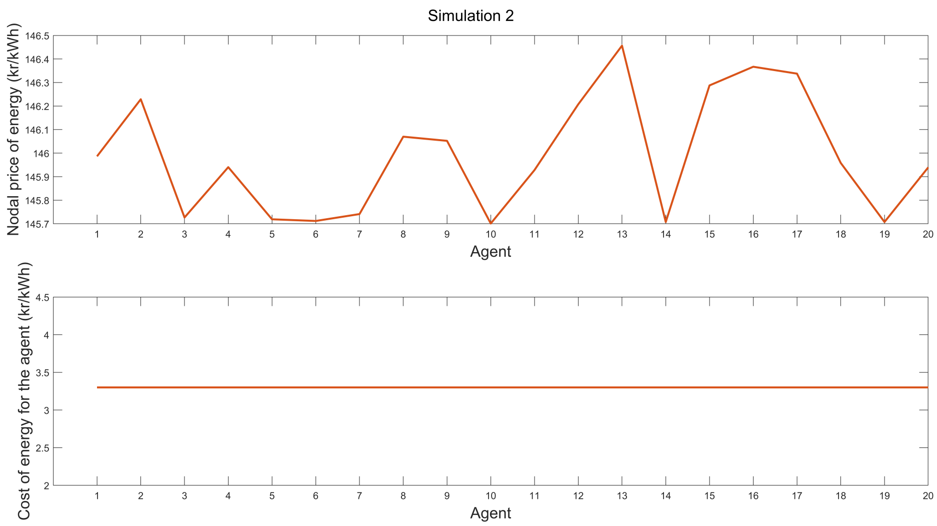


Figure 5.1: Cost of energy for the agents in the local pricing scheme. Simulation 3.

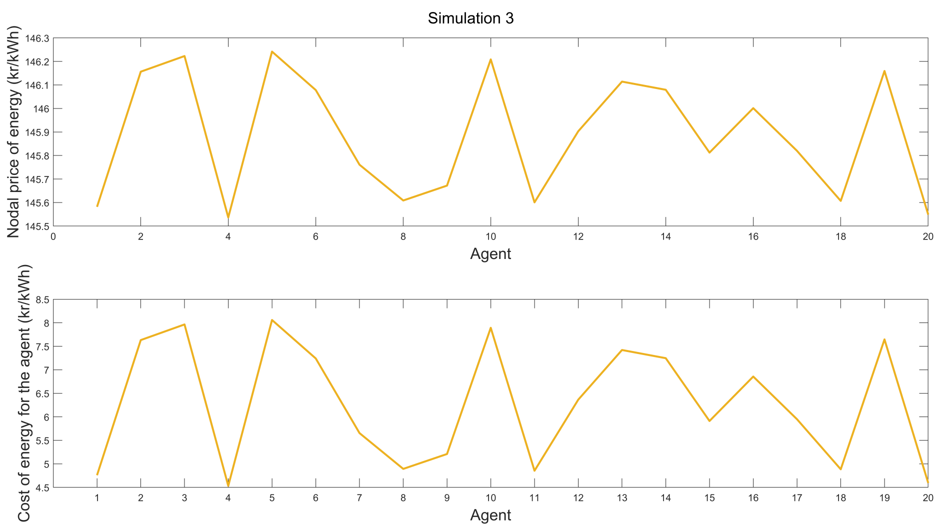
This follow-up of the real cost of energy in the price the agents pay, can be reassessed by comparison with the two other strategies in Figure 5.2.



(a) Uncontrolled



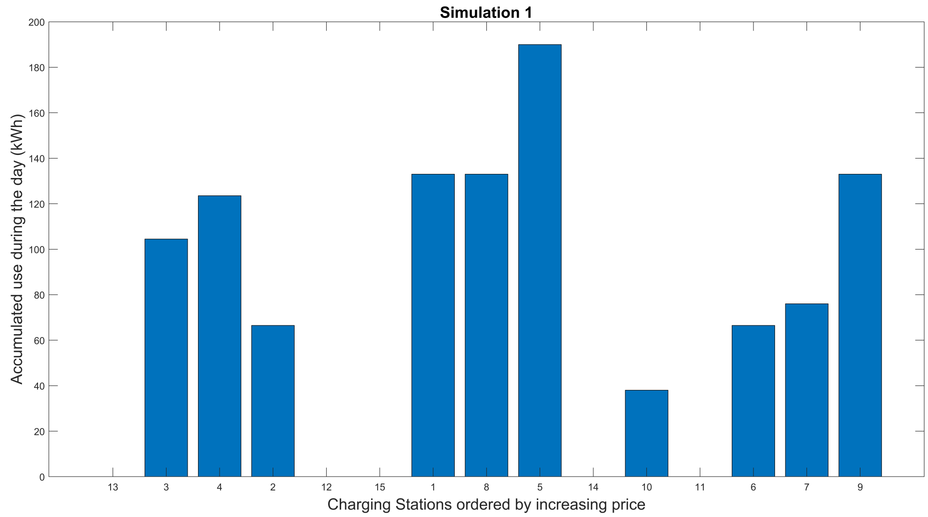
(b) Centrally-controlled



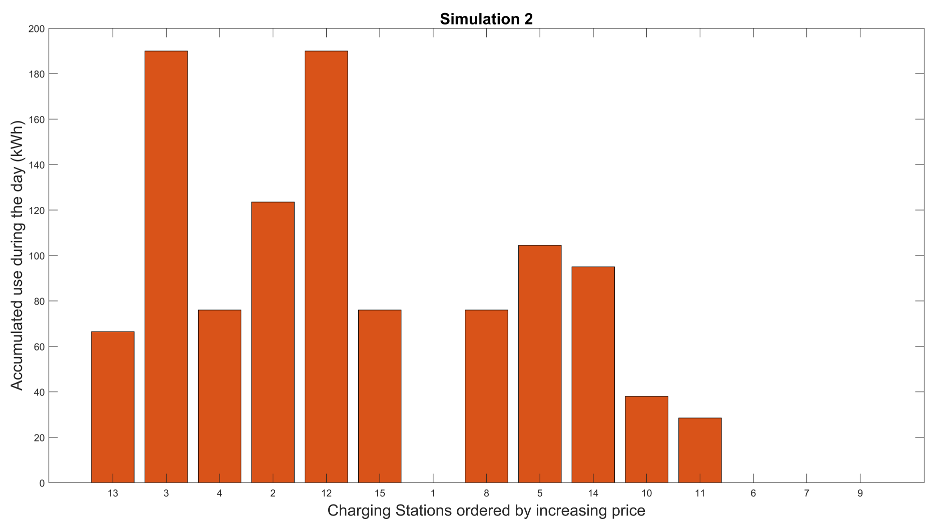
(c) Decentrally-controlled, Local pricing

Figure 5.2: Price responsiveness for the different charging strategies.

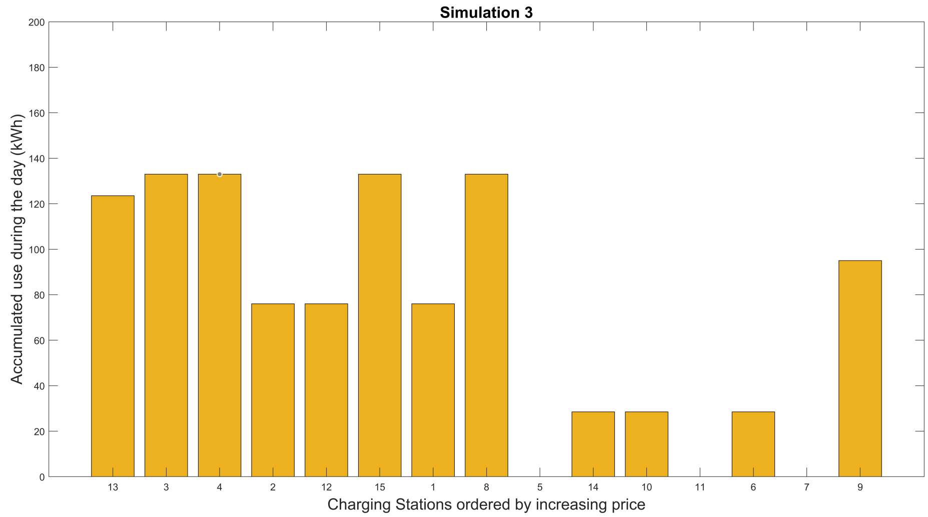
These price differences influence the choice of station that the agents make. If we sort the stations by nodal price of energy, and accumulate the use of each of them, we can compare the choices in the three charging strategies.



(a) Uncontrolled



(b) Centrally-controlled



(c) Decentrally-controlled (Local Pricing)

Figure 5.3: Use of station sorted by increasing price of energy (nodal price)

It is possible to appreciate in Figure 5.3 how different charging strategies induce different choices in the agents: In the centrally-controlled (5.3.b), agents are indeed always assigned the stations with the lowest cost of energy (nodal price), and the demand is therefore concentrated to the left, among the cheapest stations. The opposite is the case of uncontrolled decentral operation (5.3.a), where the demand is concentrated in the most transited stations. If we refer to Figure 3.10, we can verify that stations in the city center, closer to the workplaces of the agents, are the most used regardless of the price of energy.

Finally, the local pricing scheme (5.3.c) seems to distribute the demand over a larger set of stations comparing to the centrally-controlled operation, and therefore avoiding the accumulation of agents in a single station. The demand is however also concentrated to the left among the cheapest stations, doing a trade-off between the agents' interest in paying the least for the closest stations.

In view of the results presented for the simulations running a fixed set of 20 agents, it can be concluded that the scheme of local pricing economic signals to the agents, can spatially-relocate the demand of EV charging, and reduce costs of energy by sending the appropiate economic signals to the agents, who will consequently avoid the stations with the most congestion and losses costs.

5.1.2 Large randomly-generated set of 100 agents(Simulations 4-6)

In this simulation set, using a larger number of agents and over several days, we intend to prove the efficiency of local pricing when relocating energy over time, i.e., fostering charging when energy cost in the system is lower, and preventing it when the cost is higher. This alligns with the purpose of integrating a higher share of variable renewable energies in the network (see section 2.3.2).

To do so, we can start by looking at the market price of energy over the 15 days of simulation in Figure 3.3. Nevertheless, prices in Nordpool zone DK2 are quite varying throughout the same day, therefore, instead of taking a single average market price per day, we can take two prices that correspond to the market price at the times of charging. All agents charge either on their way to work or back (3.5.2), which correspond to the hours in the day between 7:00-9:00 (morning) and 14:00-16:00 (evening). In Figure 5.4 we can verify that some days maintain quite a regular price, such as day 5. Others, on the contrary, have significant variations such as day 6. For that reason, splitting the daily energy price into two time windows proves to be more illustrative for later comparisons.

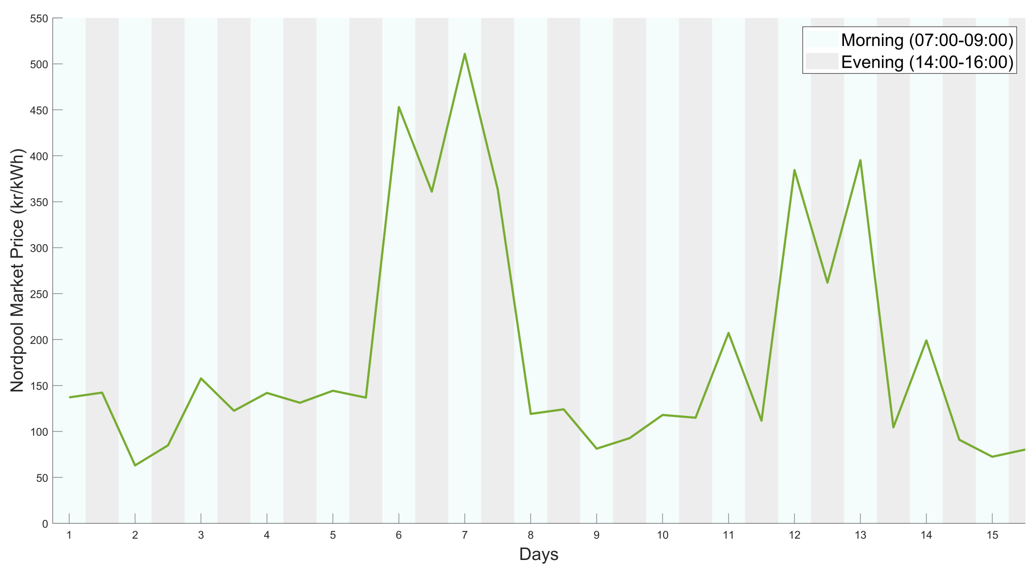
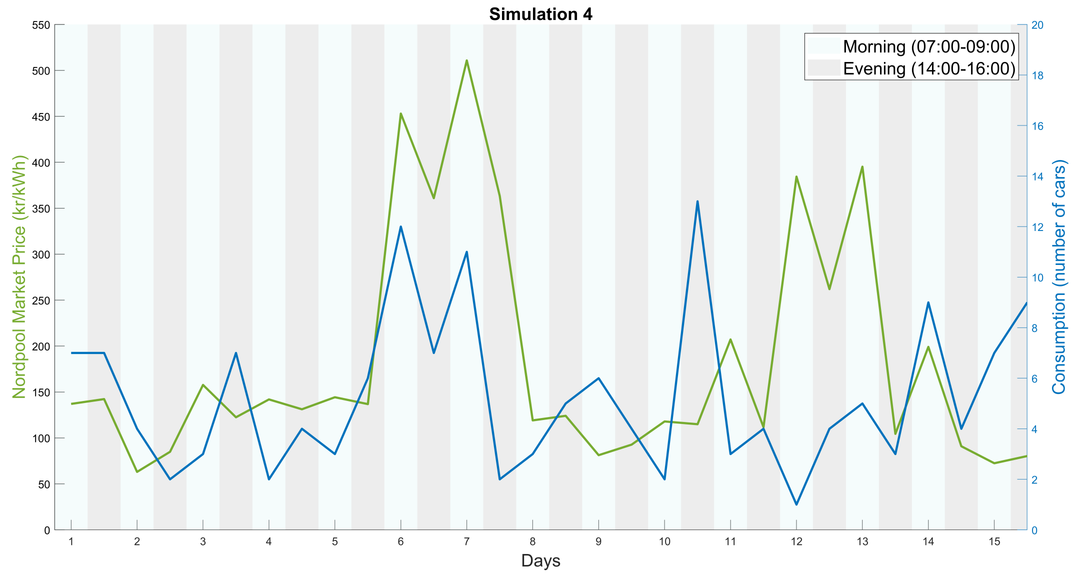
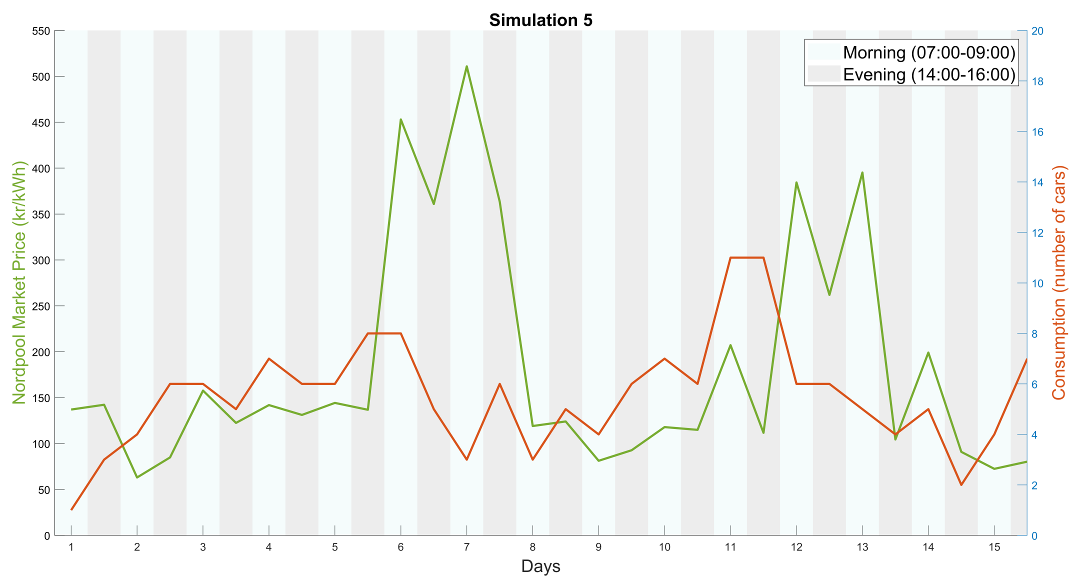


Figure 5.4: Morning and evening energy market prices over the 15 of simulation (February 8th to February 24, 2020) (AS [a])

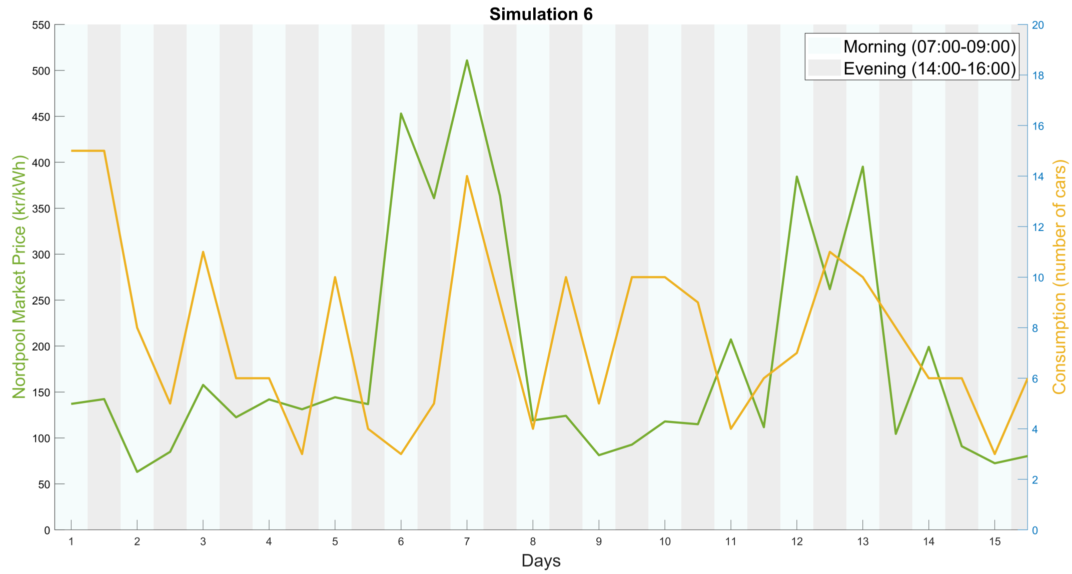
Now, we can compare how different strategies induce a relocation of the demand in terms of the market price of energy, by overlaying the daily demand for each strategy.



(a) Decentralized, uncontrolled



(b) Centrally-controlled



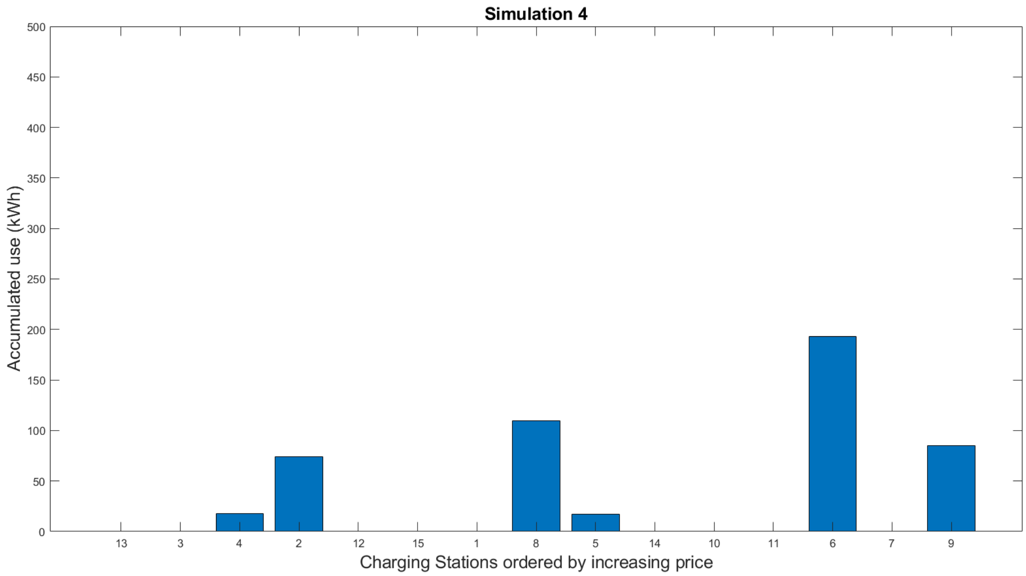
(c) Decentrally-controlled, local pricing

Figure 5.5: Daily consumption over 15 days of simulation for each strategy.

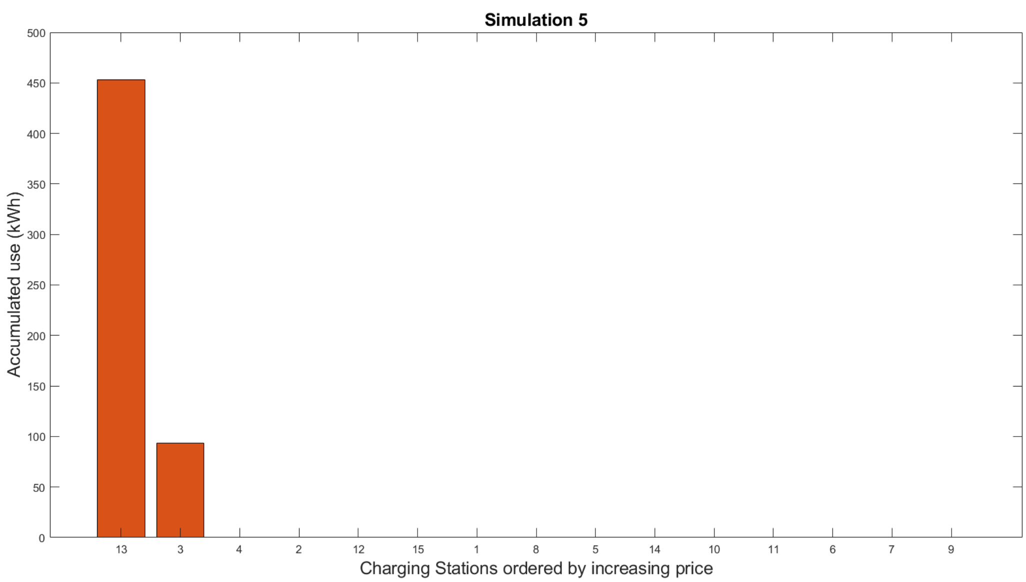
We can see how the consumption (in charging events) does not respond to changes in the market price of energy in strategies where the price for the agent is static (Figures 5.5.a and 5.5.b). Both consumption profiles show increases when the price increases, and vice-versa.

On the contrary, we can see how the demand reacts to the changes in energy market price in the local pricing scheme(5.5.c). Even if some days do not follow the rule, consumption increases when the price goes lower with respect to the previous day, and decreases when the price goes higher than the previous day. Agents willing to charge, will first check the price of the stations they can reach in their way and then decide whether to charge and where (see section 3.5.2). By avoiding charging in the days where the energy is higher, there is a long-term saving in the cost of charging energy for both the provider and the consumer. In the smart integration of the EV fleet within the grid, this is the kind of responsive behavior we are looking for.

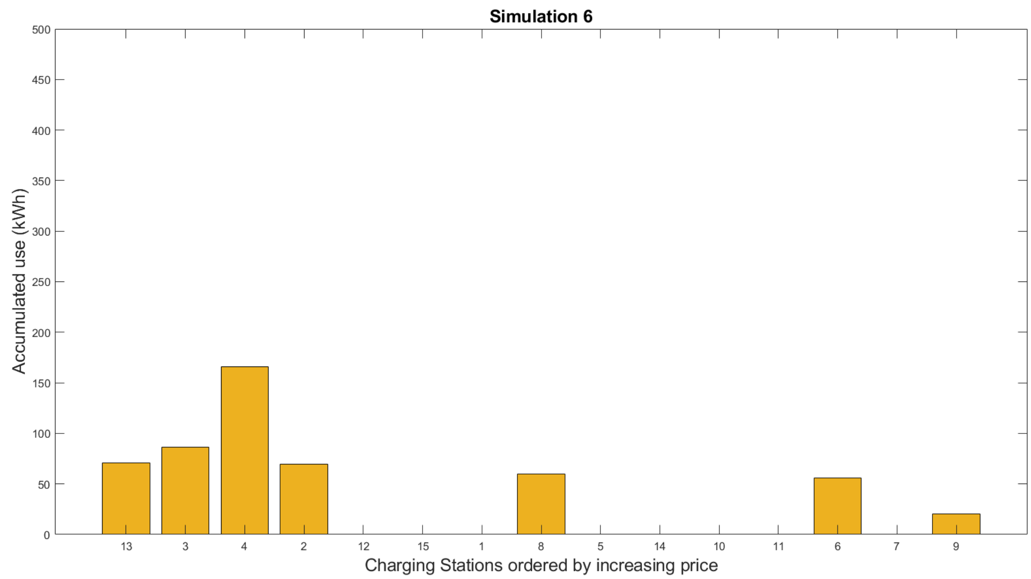
As for the case of a reduced set of agents, we can see how the strategies influence the choice of stations in Figure 5.6.



(a) Decentralized, uncontrolled



(b) Centrally-controlled



(c) Decentrally-controlled, local pricing

Figure 5.6: Accumulated use of the stations, ordered by increasing price.Simulations 4 to 6.

The differences between the charging strategies are even more flagrant in these simulations run with a larger set of agents. For the case of uncontrolled decentral operation (5.6.a), the stations at use are only those placed in the city center, nearby the agents' work locations (Figure 3.10). On the contrary, the only two stations used in the centrally-controlled scheme are those who always show the lowest cost of energy in the grid, even though station 13 is quite far from all the location of all agents, as it is placed on the highway right branch of the city (Figure 3.10).

Once more, the local pricing scheme (Figure 5.6.c) shows the most distributed consumption among the stations, by sending economic signals on the price of energy that encourage agents to make a trade-off between utility (distance to the station) and price of energy. The demand, as opposed to the uncontrolled scenario, is shifted to the left, as trying to exploit the cheapest stations first and avoid those with higher nodal prices and therefore cost of the energy (due to congestion and losses).

Finally, we can summarize the results and see if the local pricing strategy brings savings in terms of the cost of energy over this period of time. By adding all demand over the 15 days, and the price paid for each kWh charged in the fleet of EVs, we obtain the following average values:

Table 5.2: Results summary for simulation scenarios 4-6

	Charging Strategy		
	Decentralized uncontrolled	Centrally-controlled	Decentrally-controlled (LP)
Total energy consumption [kWh]	4601	4876	5428
Average cost of energy for the grid (nodal price) [kr/MWh]	200.59	172.82	131.35
Average cost for the agent [kr/kWh]	3.3	3.3	2.70

The local pricing strategy has proven to decrease significantly the price of charging for both the provider (nodal price of energy in the grid) and the consumer. In comparison with an uncontrolled decentral operation, local pricing implies a decrease of 34.5% of the cost of energy for the provider. From the point of the drivers, the mean price of energy is also reduced, even though they may sometimes pay higher than the static 3.3 kr/kWh of the other two strategies.

We can at this point conclude that, local pricing at EV charging stations, by sending the agents proportional economic signals of the actual nodal cost of energy, reduces the charging cost for both the provider and the consumer, reducing losses and congestion costs in the network. In other words, it is capable of relocating demand in the short term (spatially among the cheapest stations) and temporally (following the system price fluctuations).

5.1.3 Summary

By combining all results aforementioned, we can summarize the effect of each charging strategy

Table 5.3: Summary of the effect of the three proposed charging strategies

	Charging Strategy		
	Decentralized uncontrolled	Centrally-controlled	Decentrally-controlled (LP)
Short term demand relocation (in space, putting first the stations less congested and with less losses)	NO	NO	YES
Long term demand relocation (over time, fostering the coordination with the system fluctuations)	NO	NO	YES

Which, in terms of savings, implies:

Table 5.4: Effect of the proposed strategies on the overall cost of energy

	Charging Strategy		
	Decentralized uncontrolled	Centrally-controlled	Decentrally-controlled (LP)
Energy cost reduction for the supplier	NO	YES	YES
Energy cost reduction for the consumer	NO	NO	YES

5.2 Side benefits of local pricing

By means of this charging strategy, we have also achieved other two benefits in the charging operation of the EV fleet:

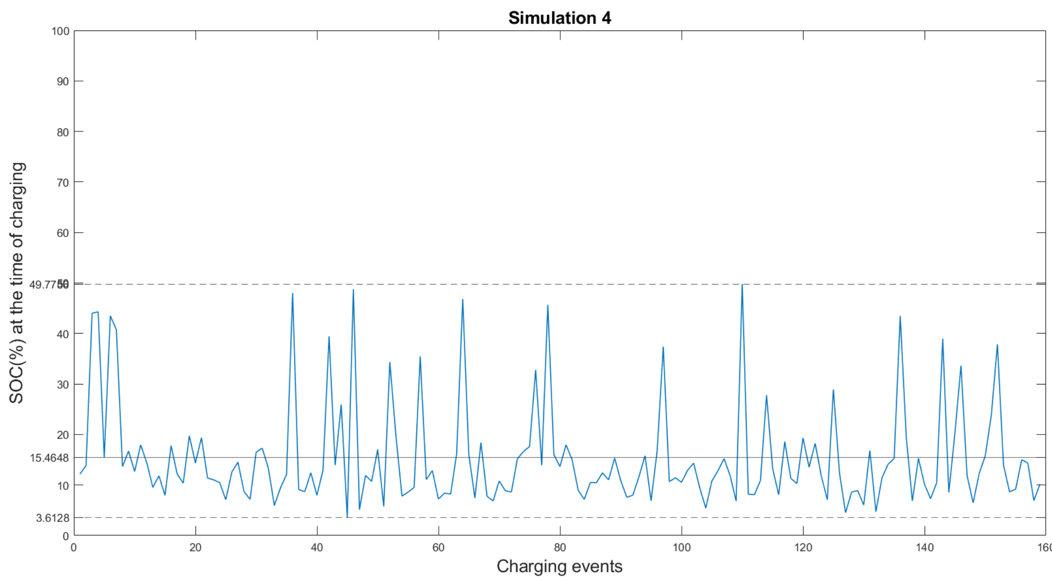
5.2.1 Improving battery cycles

When the price at the stations is static, agents charge whenever they have the need to, so they will always drain their batteries before charging because there is no point in relocating the charging over time.

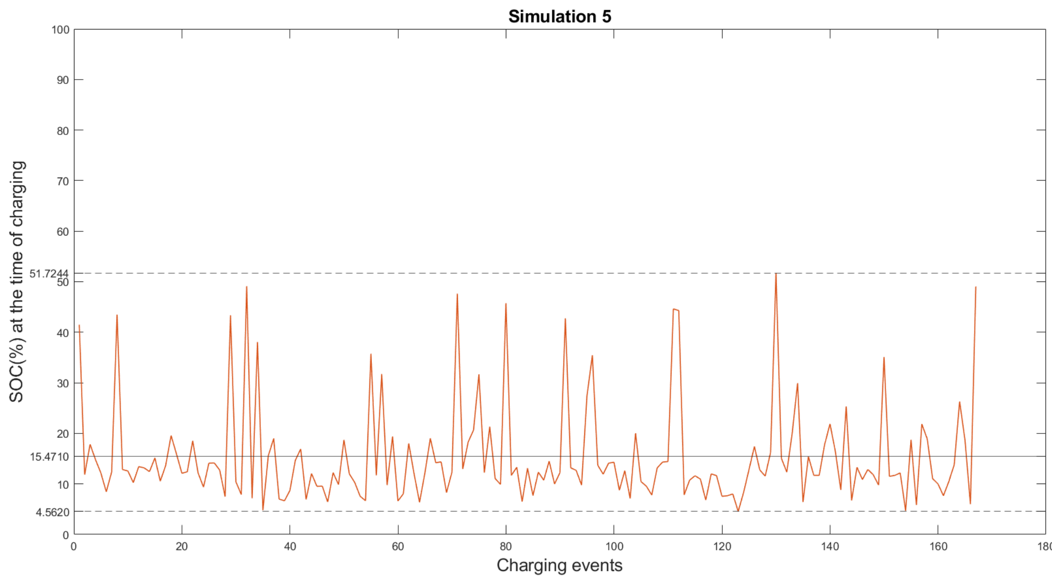
Specifically, in these strategies where the price is static, agents will charge when their SOC is below their minimum desired level of battery (SOC_{min}).

On the contrary, when the price of energy varies though time, agents might consider to either charge before they drain their batteries, or even wait longer to charge. By doing so, we are augmenting the SOC range within which the agents charge. It has been proven that charging Li-Ion batteries by non-exhaustive cycles, can extend their life

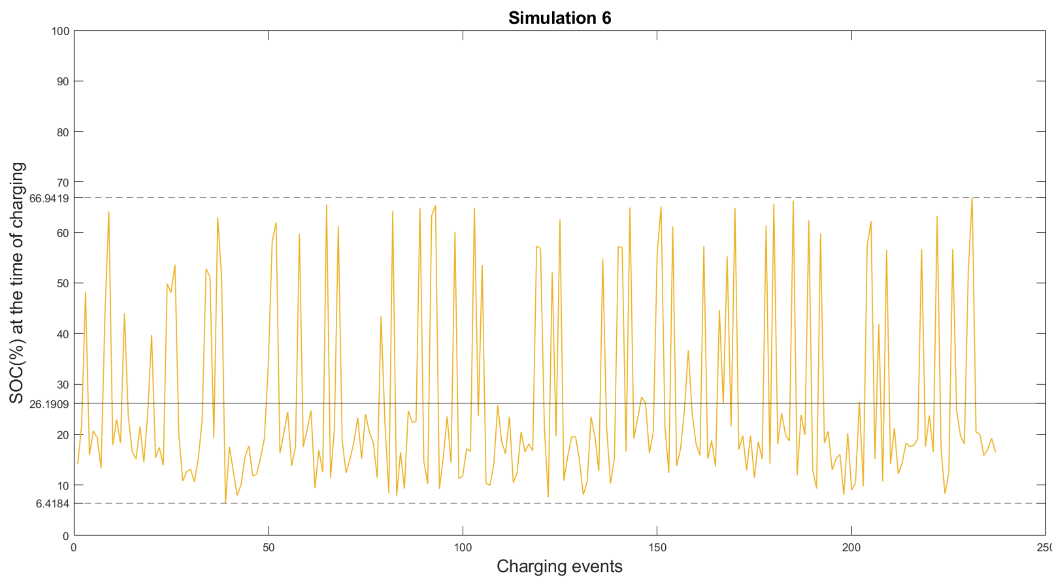
We can have a look at the SOC at which the agents charge by comparing the three strategies:



(a) Decentralized, uncontrolled



(b) Centrally-controlled



(c) Decentrally-controlled, local pricing

Figure 5.7: SOC range at the time of charging.

Effectively, agents tend to drain less their batteries when the price of energy is variable over time, charging their vehicles when their SOC level is in average 26% and not 15% as in the previous two strategies.

5.2.2 Larger benefits for the infrastructure provider

One might think than by decreasing the social cost of energy, the charging infrastructure provider has less profit margin, but the result is the complete opposite. By encouraging agents to charge when the energy price is lower, and fostering the use of less congested stations, the infrastructure provider is also incurring in smaller costs for bringing energy to the stations in use.

If we take the cost of energy (nodal prices) and the price paid by agents in each scenario from Table 5.2, we can see that in average, the service of charging incurs in a cost 20 times higher than the original cost of energy from the grid. However, the local pricing scheme is the one with the largest profit margin for the infrastructure provider, as seen in Table 5.5:

Table 5.5: Charging station infrastructure provider profit margins with different charging strategies.

	Charging Strategy		
	Decentralized un-controlled	Centrally-controlled	Decentrally-controlled (LP)
Mean cost of energy for the grid (nodal price) [kr/MWh]	200.59	172.82	131.35
Mean cost for the agent [kr/kWh]	3.3	3.3	2.70
Profit margin in times paid the cost of the energy	16.5	19.1	20.56

In conclusion, by avoiding extra costs of charging for higher prices of energy, we are not only reducing costs for the grid and the consumers, but also increasing the profit margin for the charging infrastructure provider.

6 | Concluding remarks and future research

In this chapter, we discuss the findings from the work previously presented, and indicate some lines of research to pursue development in this topic.

6.1 Assessing the potential benefits of LMP smart pricing strategies

This thesis studies the opportunities offered by LMP-based smart pricing strategies in order to optimize EV charging operation, and by the comparative study developed in section 5, we can conclude:

- Locational Marginal Pricing is an effective scheme to reflect the actual cost of energy at every node of the grid, where the charging stations are located. This market configuration, by increasing granularity in both time and space, gives real-time economic signals based on the energy generation and local network constraints.

- On the temporal dimension, LMP can follow the generation variability of renewable sources (system marginal price, first component, see figure 2.10), such as wind or solar energies. By doing so, charging becomes more expensive at times of limited generation, and cheaper at times of surplus. In response, agents relocate their charging over time, and they tend to avoid times of higher prices.

  Considering their charging preferences (behavior), some agents will prefer to charger sooner even if the price is high, based on their actual SOC and their range anxiety. Some other agents will try to wait to lower prices and will react to price decreases by augmenting the demand.

  By doing so, the EV demand of energy is improving the demand flexibility, and facilitating the introduction of variable renewable energies, as suggested in the innovation landscape for market design proposed by IRENA [2019a].

- On the spatial dimension, LMP is also able to reflect congestion and transmission losses within the local distribution grid (second and third components see figure 2.10).

  Before leaving their current location, agents in our model will consider the possibility of charging if their battery is below a certain level, and if the prices are within the agent's willingness to pay. Then, the agent will choose an itinerary incluiding the charging station that best fits its preferences. By means of charging the energy upon LMP , the prices will vary from one station to another, depending on congestion and transmission losses. Agents will therefore try to incorporate to their itinerary the stations with the least congestion and losses cost.

  This entails a more stable and safe operation of the system, avoiding congestion in only some stations of the set, encouraging distributed use, and sparing costs for the agents and for the grid operator.

  This way, the growing share of electric vehicles is better managed, and the grid will have a grater hosting capacity in consequence (see section 2.3.3).

- Altogether, we can affirm that applying LMP schemes to the EV charging stations, can foster the voluntary (decentralized) relocation of the demand, in both time and space, without the need of gathering and computing the data of the agents like in a centralized control strategy. This requires a less-demanding communication infrastructure and computational capacity, by delegating responsibility in each agent and not in the central aggregator. It also prevents the agents from sharing their route information, vehicle state or preferences, which may be seen as a privacy violation by many.

- Reflecting the actual cost of energy fosters the efficient demand among users, and this brings two main side benefits:

  - The agents do not drain their batteries before planning to charge, since they can charge beforehand if the price of the system is low. This improves the life span of batteries, by not discharging deeply.

  - The agents' interest of charging when the energy is cheaper aligns with that of the network and the infrastructure provider. By decreasing costs for all parties involved, the infrastructure provider has a grater profit margin too, even if both the grid and the agents have seen their costs reduced. Optimization methods should

6.2 Future research

This thesis presents very promising results regarding the introduction of dynamic local pricing schemes for the charging of electric vehicles. However, the model and the simulation cases aforementioned are limited. We can outline some of the limitations of this study, and propose future work on this topic that could enlarge the assessment of this smart charging strategies:

- The price scheme that was built in this analysis was just one proposed example of how the system price and the local network constraints can have an equal weight on the price paid at the stations. However, the pricing scheme of the stations operator is key in optimizing costs and making the charging energy affordable and just. Its optimization is subject of a further study that should include artificial intelligence to improve the identification of the agents' behavior patterns, in order to optimize operation based on a short-term forecast of both the demand and the market fluctuations.

- The interface between the agent-based model of the drivers' behavior (coded in JAVA) and the solving of the grid constraints formulated in an OPF problem (modelled as a case in Zimmerman and Murillo-Sánchez [2019]) was the bottleneck of computational speed in the simulation tool used in this thesis. Improvements could be made if the OPF problem could be formulated in JAVA without the need of resorting the synchronous console running of two different software. The same combination of models could be made in Python or any other language that is fit for object-oriented programming. A faster interface could have allowed the simulation of a greater number of agents, which is another limitation of this model.

- Energy storage (owned by either the grid or the consumers) and local generation (mainly solar power) are gaining great relevance in the way towards optimizing the introduction of variable renewable sources in the grid. They were not considered in this work for the complexity they entail, introducing more dynamics into the system to optimize. They have been the scope of a number of preceding master thesis within this department (Lillebo et al. [2019], Sagosen and Molinas [2013] and Harbo et al. [2018]), and combining the dynamic local pricing market with the opportunities they offer, is a field to be explored undoubtedly.

- This thesis only considered fast charging stations in the grid, with a power up to 150 kW. It was done this way for the growth that public charging infrastructure is seeing, and for the higher charging rates that vehicles now incorporate. This was intended to represent a worst-case scenario where all EV owners charge at fast charging stations where the network is the most constraint. However, a combination of slow charging (at home or work) and fast charging (along the city paths, or at public facilities) is a more realistic scenario that could be modelled.

- The simulation tool used in this thesis was merely approachable by means of an on-screen console. It would have been easier to visualize results if the real-time output of this model had been dumped in a GIS software. A software of this kind was used indeed to visualize the city spaces and layout. Open-source GIS software allow Python programming to integrate them with other applications such as this model, which opens the door for building a more user-friendly interface that could help assess the impact of charging strategies in the city dynamics and costs of energy.

- Finally, we can also acknowledge that the charging and discharging dynamics of the electric vehicles were quite simple in the model presented. They were approximated to linear functions of the distance travelled and the charging time. Much more accurate models of the discharging and charging dynamics of EV batteries are nowadays available, and they could make this simulation tool more realistic about the energy demand.

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Appendices

A | Agent-based model: JAVA code

The code for the agent-based model developed in JAVA, whose structure and functioning is described in section 3.5, is accessible from the GitHub public repository where it has been stored:

`https://github.com/manuep/Master_Thesis.git`

The files included in this repository are grouped as in Figure A.1.

A.1 Setting up the simulation tool

The ABM code developed in JAVA has to be downloaded and executed with a JAVA console. The integrated environment used for this thesis was Eclipse IDE for Java Developers, version: 2020-03 (4.15.0). One can freely download and use this environment from their website `http://www.eclipse.org/platform`.

The simulation tool is a coordination between this ABM model coded in JAVA and the grid model formulation solved by means of the MATPOWER (Zimmerman and Murillo-Sánchez [2019]) package in Matlab®, by adding the JAVA class `com.mathworks.engine` that uses Matlab® as a computational engine. The detailed documentation on how to use this class in JAVA can be found following the direction : `https://www.mathworks.com/help/matlab/matlab_external/execute-matlab-functions-from-java.html`.

As JAVA will call the Matlab® engine from the console, some set up steps are needed to define the start of the Matlab® program from the system prompt. The documentation for Windows in under the direction : `https://www.mathworks.com/help/matlab/ref/matlabwindows.html`.

Once we have the `com.mathworks.engine` JAVA Class running as a Matlab® console from which we can execute functions, we need to define:

- `mpc` case of MATPOWER

As described in section 3.3.1, the input data of the network has to be expressed in a `mpc` structure, whose main components can be seen in table 3.1 and the full documentation of the package in the direction: `https://matpower.org/docs/MATPOWER-manual.pdf`.

In the code hereby presented, the `mpc` case is referred as `mpc-case-file` (in the `Coord-matlab.java` file within Model → *Schedule*.

- The `mpc` case only defines consumption for a given time step. If we want to simulate a time span, we will need the historical consumption data in a separate file from which we can re-define the `mpc` case as many times as wanted. This file containing the historical consumption data is referred as `buses-consumption-data`, also within the `Coord-matlab.java` file.

- Other dimensions such as the number of buses (`n-buses`).

Then, we need to define the directory where the code files are placed, since the code will call other files in the directory, and will write the outputs also within. Future users will have to re-define the directory path in their own computer after downloading, in the following files:

  - Model → *Agent* → `Agent.java`

- Model → *Schedule* → `GlobalClock.java`

- Utils → `Variables.java`

- In every file of the directory: Utils → *Charging* → *Strategies*

After these steps, the console should be able to run the `World.java` (within Environment) as a JAVA Application.

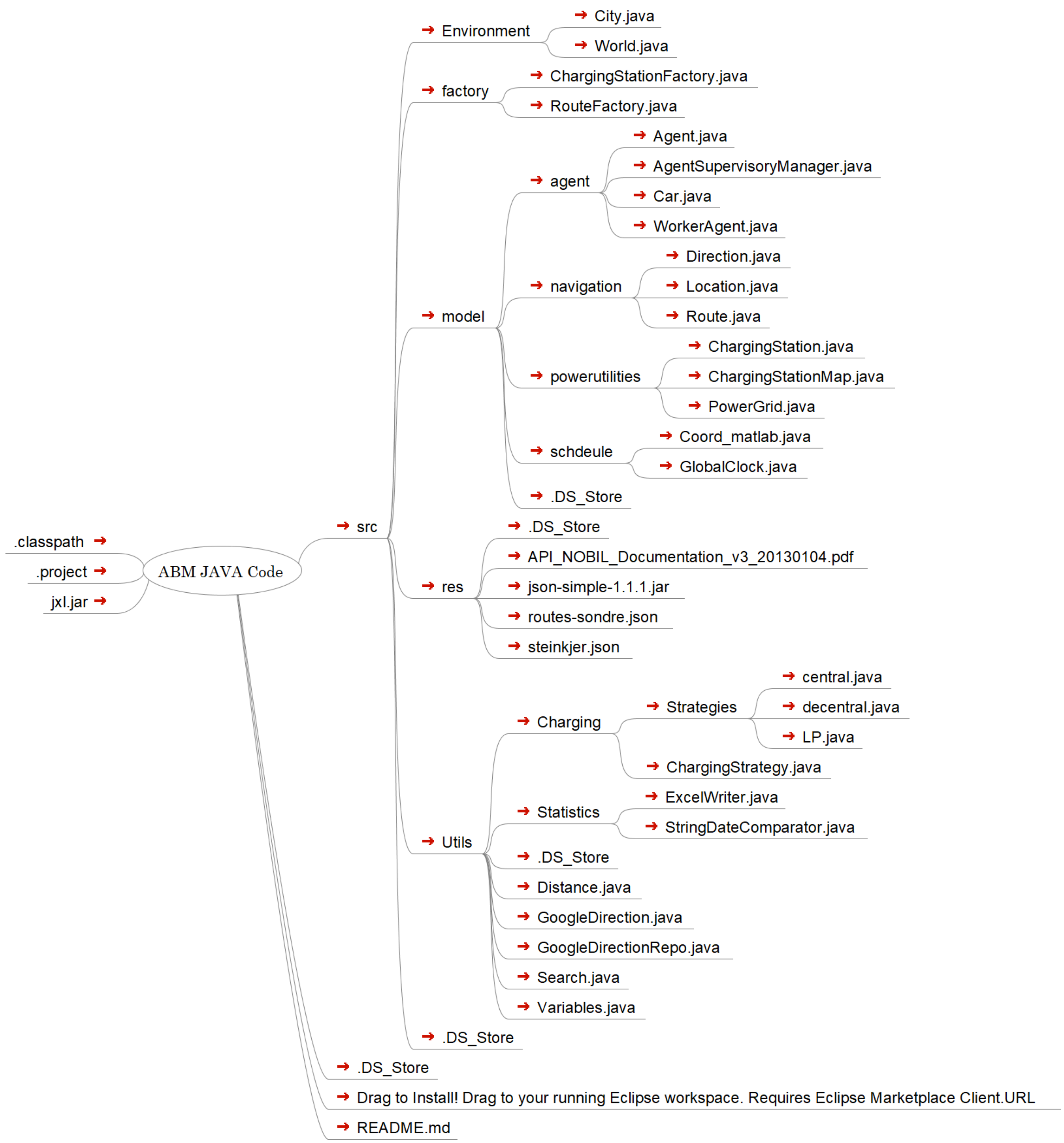

Figure A.1: Structure of files available in the GitHub repository. ABM JAVA Code.

A.2 Input

When the console runs the `World.java` as a JAVA Application, the user will have to enter a series of simulation parameters, among which we find:

- Number of agents: enter a whole number of agents to simulate.
- Number of simulation days: enter a whole number of days to simulate.
- Charging strategy: Enter "1" for centrally-controlled charging operation, "2" for uncontrolled, and "3" for decentralized control (local pricing). The charging strategies are described in section 4.

The user should see the following in the console:

Listing A.1: User input parameters for the simulation. Console view.

```
USER INPUT - Please enter the following
Number of agents:
100
Number of simulation days (2 or higher):
15
Charging Strategy? 1=Centrally-controlled, 2=Uncontrolled, 3=Decentralized control
    ↪ (Local Pricing)
3
```

After entering these parameters, the simulation should start automatically.

A.3 Output

After the simulation is finished, the code will have generated a number of files in the same folder where the code is located. All these files will be `.txt`, and they will have the following structure:

1. `agents-prop.txt` In this file, the user will find all the information regarding the definition of agents. Please refer to section 3.5.2 for information about the variables stored in each column:

Table A.1: Values of the columns stored in the file `agents-prop.txt`

Column 1	Column 2	Column 3	Column 4	Column 5
Agent ID	Maximum battery capacity	Current SOC	x_{Pr}	x_D

2. `losses.txt`

In this file, the real and imaginary components of the total losses in the network are stored for every simulation minute.

Table A.2: Values of the columns stored in the file `losses.txt`

Column 1	Column 2	Column 3
Date and time (dd-mm-yyyy, hh:mm)	Real losses	Imaginary losses

3. `satisfaction.txt`

In this file, the charging choices and consequent satisfaction level of the agents will be stored.

Table A.3: Values of the columns stored in the file `satisfaction.txt`

Column 1	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
Date and time (dd-mm-yyyy, hh:mm)	Agent ID	Station ID	Current SOC	Maximum battery capacity	Price of charging [kr/kWh]	Nodal price at the station [kr/kWh]

4. `stations-file.txt`

In the stations file, the user will find both the power consumption and the nodal price of energy at each station, every minute of the simulation. If we have m stations in the set:

Table A.4: Values of the columns stored in the file `stations-file.txt`

Column 1	Column 2...(m+2)	Column (m+3)...(2m+3)
Date and time (dd-mm-yyyy, hh:mm)	Power withdrawal at each station [kW]	Nodal price at each station [kr/kWh]

5. `voltages.txt`

Within this voltages file, the voltage magnitudes (p.u.) are registered every simulation minute and for every charging station. There, if we have a set of m stations:

Table A.5: Values of the columns stored in the file `voltages.txt`

Column 1	Column 2...(m+2)
Date and time (dd-mm-yyyy, hh:mm)	Voltage magnitude (p.u.) at each station

Note Please feel free to contact the author using the email `manperbra@outlook.es` if there were any questions regarding the code, if the GitHub access link was not working properly, or if the reader wants the case data to try the results.

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Master's thesis

2020

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