Analysis and optimisation of electric vehicle charging infrastructure in Turin using a multiple criteria facility location problem approach

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Contents

List of Figures

List of Tables

Glossary

Terminology

Battery Electric Vehicle: An electrically driven vehicle with a battery as the primary energy source.

Linear Programming: A mathematical optimisation model to either maximise or minimise a set of linearly related variables, under a set of linear constraints.

On-board Power Converter: A component of an electric vehicle, used in the drive-train and charging systems, that is responsible for the conversion between alternating and direct current, as well as the conversion from one voltage level to another.

Plug-in Hybrid Electric Vehicle: A type of electric vehicle containing both an internal combustion engine and an electric motor, with a battery that can be recharged from an external power source.

List of Abbreviations

AC	Alternating Current
API	Application Programming Interface
BEV	Battery Electric Vehicle
DC	Direct Current
DCFC	Direct Current Fast Charger
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GIS	Geographic Information System
ICE	Internal Combustion Engine
LP	Linear Programming
PHEV	Plug-in Hybrid Electric Vehicle
RFID	Radio Frequency Identification
USD	United States Dollar
ZTL	Zona a Traffico Limitato

List of Symbols

- c the assumed constant cost to build a new charging station in Turin
- i a set of squares dividing the city of Turin, representing the location being considered
- v_i a set of binary decision variables determining if location i is partially covered by charging stations
- x_i a set of charging stations located at quadrant i
- y_i a set of binary decision variables determining if location i is fully covered by charging stations

- α the lowest acceptable target coverage as a percentage of area covered by a charging station
- β a tuning variable defined as the penalty coefficient used to penalise partial coverage
- θ a tuning variable defined as the lowest coverage to be considered full coverage
- ω a tuning variable defined as the lowest coverage to be considered partial coverage

List of Units

km	kilometer
km^2	square kilometer
km/h	kilometer per hour
kW	kilo Watt

Abstract

Of the many factors hindering the mass adoption of electric vehicles (EVs), the dilemma of charging infrastructure is one of the most difficult to solve. The number of consumers willing to buy an EV are still relatively low. Most consumers are hesitant partially because of the lack in charging infrastructure, yet infrastructure suppliers are wary of large scale investments due to the low number of EV customers. This causality problem is one that is the main focus of this thesis. To begin with, an overview of the problem environment of EV adoption as a whole will be given. This will be followed up by the proposal of a linear programming model aimed at optimising the location of new EV charging infrastructure in the city of Turin (Italy), designed to minimise the total cost of infrastructure upgrades while fulfilling targeted area coverage requirements. The mechanisms contained within the program, as well as inputs, outputs, alterations and different prioritisations are discussed an analysed. The thesis concludes with a set of infrastructure upgrades that could increase the area coverage of the EV charging network in the city of Turin from 62% coverage to 90% coverage at an investment cost of €28,224, with future upgrades to the charging network being required as the number of EVs increases.

Key words: Electric vehicle, Linear programming, EV charging station, Facility location problem, Optimisation, Partial coverage

1 Introduction

One of the major causality problems hindering the adoption of electric vehicles (EVs) has been the chicken-and-egg problem of EV charging infrastructure. Consumers are hesitant to commit to buying an EV partially due to the lack of infrastructure and the providers of charging infrastructure are hesitant to invest into building more infrastructure due to the relatively low consumer adoption of EVs (Xiang et al., 2017). Beyond this, a significant number environmental, technical, economic and social problems stand in the way of EVs replacing traditional internal combustion engine (ICE) vehicles (Kurani, Caperello, and Tyree-Hageman, 2016).

This thesis aims to first, analyse the problem of EV charging infrastructure and overall factors currently hindering a more widespread EV adoption by consumers. This is done in chapter 2 by considering factors holding back the adoption of EV technologies amongst consumers and manufacturers, analysing the environmental impact of EVs, and by specifically addressing how the charging infrastructure affects the EV market. In chapter 3, an overview of the possible solutions to the charging infrastructure problem will be given, as well as a discussion of the methodology that was chosen to be implemented for this thesis. More specifically, an optimisation model aiming to reduce overall cost of a more extensive EV charging network will introduced in chapter 4. This linear programming model takes the city of Turin as an example to analyse existing EV charging infrastructure and uses a model similar to the one used by (Huang, Kanaroglou, and X. Zhang, 2016). Chapter 6 will focus on the output of the model, which is a set of possible EV charging locations that fulfil a certain coverage goal while minimising the investment cost required to build them, to help alleviate the aforementioned causality problem. Furthermore, possible changes and future extensions of the model are discussed in sections 5 and 7.2.

2 Problem Analysis

2.1 The Consumer Adoption Problem

The purchase of an electric vehicle is a difficult decision for many consumers, that so far few people have made, as can be seen by the case of Italy where the market share of EVs was at only 0.5% of all vehicle registrations in 2020 (Danielis et al., 2020). This section will analyse how consumers view EVs, and which objective and perceptive issues limit the widespread adoption of these vehicles. The most common concern amongst consumers is the range of electric vehicles when compared to traditional ICE vehicles (Kurani, Caperello, and Tyree-Hageman, 2016). Commonly referred to as "range anxiety", many consumers are hesitant to buy an EV, since the limited driving range of a single battery charge combined with the long charging time (compared to the refueling time of ICEs) would significantly lengthen the travel time for long distance journeys (Bonges and Lusk, 2016). This problem is also related to the limited amount of charging points available to EV owners (Hardman et al., 2018), however the issue of charging infrastructure will be discussed more thoroughly in section 2.3.

In addition to the limitation of the maximum range, a number of other factors also dissuade many consumers from purchasing an EV. In fact, while consumers rate the range as the most common reason for them to not purchase an EV (Kurani, Caperello, and Tyree-Hageman, 2016), a quintupling of the battery size would only lead to a five percent increase in consumer adoption (Adepetu and Keshav, 2017). As such, multiple factors impacting the buying decision of consumers need to be improved for electric vehicles to be adopted, including the range and the purchasing cost (Adepetu and Keshav, 2017). The pricing of EVs was also an issue for many consumers (Kurani, Caperello, and Tyree-Hageman, 2016). The average purchase price of a fully electric vehicle was 42.6% higher than an average ICE vehicle (Coren, 2019). This high price means that consumers were also significantly less likely to purchase an EV (Rezvani, Jansson, and Bodin, 2015), without the addition of subsidisation to reduce the overall purchase price, as well as other government incentives it is likely that the adoption of EVs will be strongly impacted (Xiang et al., 2017). This is despite the fact that consumers tend to save costs in the long run when owning EVs, a fact that a majority of consumers were not aware of (Rezvani, Jansson, and Bodin, 2015), meaning that the high purchase cost still impacts the purchasing decision more than the long term running costs. Once this early stage of EV adoption has been overcome, where the purchase price no longer has a dominant impact on the purchasing decision, different factors such as the state of technology and infrastructure will become the dominant factors affecting the evolution of the EV market (Xiang et al., 2017).

Hesitation from automotive manufacturers to commit to the development of EVs has also been a point of concern amongst consumers, with automotive manufacturers potentially being wary of the high development costs associated with a radically different technology such as EVs (Xiang et al., 2017). As such, while the ICE clearly remains the dominant design within the automotive sector, battery electric vehicles (BEVs) haven't even been established fully as the dominant design within the "environmentally sustainable" automotive segment. The case of Toyota is a clear example of this uncertainty in the BEV technology, and the effect it can have on the manufacturers. Toyota was an early innovator in hybrid-electric vehicles, with a strong and lasting interest in manufacturing cars with a lower environmental impact than ICE vehicles (Hawkins, 2021). With the Toyota Prius being the first mass-produced hybrid-electric car in 1997, Toyota found a great degree of success in the small but growing non-ICE segment (Toyota, n.d.). Currently 80% of Toyota's vehicle lineup is being offered with the option of a hybrid-electric powertrain (Lyon, 2021), however Toyota is still hesitant to fully commit to the BEV technology as opposed to hybrid and hydrogen powered fuel cell electric vehicles (FCEVs) (Toyota, 2021). Toyota has committed to a vehicle lineup consisting of ICE, full hybrid EVs, Plug-in hybrid EVs (PHEVs), full BEVs and FCEVs (Toyota Magazine, 2021), from which it can be inferred that at the current point in time Toyota is not confident that full BEVs will establish themselves as the dominant technology in the long run. As such, Toyota is hedging their research and development investments between different ICE alternative technologies until it is clear what form of propulsion will become the dominant design in the long run for personal vehicles (Davis and Inajima, 2021). The case of caution due to uncertainty in the technology is not exclusive to Toyota, where currently PHEVs are considered as a bridge technology until BEVs become established as the dominant design within the industry (Xiang et al., 2017). However, increased rivalry in the market and greater dispersion of the technology will further BEV development from manufacturers in the long run (Wesseling, Faber, and Hekkert, 2014).

2.2 The Environmental Problem

From a societal point of view, the end-goal of electric vehicles is to have a lower environmental impact with lower greenhouse gas emissions than conventional ICE vehicles. While some consumers picture an environmentally benign and emission free vehicle, the reality of the environmental impact of EVs is slightly more complicated. When quantifying the environmental impact of a product, it is common practice to consider the impact of the production, the use phase and the disposal of a product using a variety of different performance indicators such as energy consumption of greenhouse gas emissions (ISO, 2006). A large variety of studies have been performed on the impact of EVs over the life cycle compared to ICE cars, from early adopter stages of EVs and more modern ones (Wang, Tang, and Pan, 2017; Faria, Marques, et al., 2013; Notter et al., 2010; Leuenberger and Frischknecht, 2010; Faria, Moura, et al., 2012), from which a number of conclusions can be made. For the case of both ICE and EV cars, the majority of greenhouse gas emissions result from the use phase of the car (Faria, Marques, et al., 2013), as such the emission of the vehicle during operations has the largest impact on the environmental "friendliness" of a vehicle. In the case of EVs, the source of the electricity generation has a great impact on the life cycle emissions of the vehicle. In countries where a majority of electricity is generated from fossil fuels, the total greenhouse gas emissions associated with the use of an EV is substantially higher than in a country where more renewable energy sources are used to generate electricity (Faria, Moura, et al., 2012). In Poland for example, the Smart Electric Drive has a higher CO_2 emission per km than its diesel-powered counterpart since the Polish electricity mix is heavily focused on fossil fuels. In France however, where more electricity is generated from non-fossil fuel sources, the Electric Drive Smart car has a lower CO_2 emission per km than a diesel powered Smart (Faria, Marques, et al., 2013). As such, it can be concluded that EVs alone are only an effective tool in reducing environmental impact of greenhouse gas emissions, if the widespread adoption of EVs coincides with a shift in energy policy toward renewable energy sources. In China for example, a country where EV adoption is relatively high (Wang, Tang, and Pan, 2017), the lifetime greenhouse gas emissions are actually higher than the emissions of a typical ICE vehicle. Therefore a higher EV adoption rate in China has a negative impact on the environment given the current electricity mix (Ajanovic and Haas, 2018).

Beyond the usage of the vehicle, the manufacturing process has the second highest environmental impact (Faria, Marques, et al., 2013), with the EV manufacturing being significantly more impact than an ICE vehicle mainly to the battery. For EVs, the greenhouse gas emissions resulting from the battery production are typically comparable to the emissions resulting from the production of all other vehicle components combined (Faria, Marques, et al., 2013). The production of both the raw materials and the battery itself are very energy and resource intense processes (Meshram, Mishra, Sahu, et al., 2020). Lithium ion batteries, which is the most common battery type used for electric vehicles, require a large amount of effort to be recycled effectively. Much research is being conducted to make these recycling processes more effective and efficient (Meshram, Mishra, Sahu, et al., 2020). As a result of these recycling challenges, only 5% of lithium ion batteries are recycled in the EU (Ajanovic and Haas, 2018), despite the fact that the lifetime greenhouse gas emissions associated with a lithium ion battery are reduced by up to 50% when using recycled raw materials (Dunn et al., 2012). Additionally, the extraction of virgin raw materials used in lithium ion batteries has a severe environmental impact beyond just the energy consumption and greenhouse gas production. Specifically, the extraction of lithium requires large amounts of water, while simultaneously polluting the remaining water supply to the point where it has become harmful to humans and is having long-term adverse health effect on the local population (Concha et al., 2010).

To summarise, electric vehicles currently are not a solution to reducing the environmental impact on society. In fact, an increase in EV usage can have a more severe impact on nature as well as bringing in new environmental problems. It is therefore crucial that advances are made in electricity production, battery design, production processes and recycling efforts. Only when these are improved can the widespread adoption of EVs reduce the environmental impact of the general public.

2.3 The Charging Problem

As already mentioned in section 2.1, the current charging infrastructure is significantly slowing down the rate of adoption of EVs. It is already established that consumer adoption of EVs is still low in Italy (Danielis et al., 2020), which results in the few companies that provide public EV chargers to have a low revenue from these chargers as they are being used by only a small amount of consumers. These companies are then hesitant to invest any further into new EV chargers since they yield a low return on investment. As such only a low number of public EV chargers are available to the public, which in turn dissuades potential EV buyers thus exacerbating the EV charger problem. With this chicken-and-egg problem affecting infrastructure providers and consumers, governments have attempted to address this problem with targeted investments on both ends of the supply and demand curve (Hardman et al., 2018). This strategy has resulted in a large variety of subsidies and tax incentives being given to both infrastructure providers and EV buyers, in order to accelerate the adoption of the technology (Lorentzen et al., 2017). This problem and its alleviation will be the main focus of this thesis. By presenting a cost effective way to make public chargers available to consumers, the charger availability problem can be partially mitigated. Despite this, consumers also need to be made aware of the availability of public chargers available to them. This lack of readily available information on charging point locations, as well as confusion amongst consumers on where to find public chargers exacerbates the problem further (Kurani, Caperello, and Tyree-Hageman, 2016).

The confusion amongst consumers goes beyond the location of chargers. Many of their worries can be attributed to a lack of standardisation within the industry. In addition to the problem of locating a charger, consumers are also faced with incompatibility in charging ports for their EVs. The traditional alternating current (AC) charging has seen some form of geographical standardisation, with SAE J1772 type 2 charging ports becoming standard in the North American market and Japan and EU regulations requiring a type 2 charging port as the standard (Hall and Lutsey, 2017). However, in regions where the charging plug type is not regulated however, companies are able to use proprietary connectors, like in the case of Tesla who uses a proprietary connector for both AC and direct current (DC) charging in North America. This is because they wish to differentiate their cars by providing access to a network of DC fast chargers (DCFCs) branded as "Superchargers", that is not available to non-Tesla cars (Tesla, n.d.(a)). This exclusivity of charging stations if enforced by the proprietary connector in this case.

However, regulations can free up this type of proprietary use to provide additional utility to all consumers (Lorentzen et al., 2017). This approach of regulating a standardised port has proven effective, with Tesla relinquishing exclusivity of their "Superchargers" due to the type 2/ CCS port requirement in the European market (Tesla, n.d.(b)). Another key attribute lacking standardisation is the payment system, with a common system being radio frequency identification (RFID) payment cards exclusive to the provider of the public charge point, leading to customer confusion about the compatibility of their payment options (Kurani, Caperello, and Tyree-Hageman, 2016). However, efforts have also been made to overcome this issue with Norway introducing a standardised RFID tag payment as well as payment over SMS or mobile apps (Lorentzen et al., 2017), and with the US state of California mandating credit and debit card payment options on all public EV chargers (Hardman et al., 2018).

The problem currently referred to as "range anxiety", also has its roots in a lack of charger availability, more specifically due to the lack of DCFCs on long range travel routes (Kurani, Caperello, and Tyree-Hageman, 2016). The concern that consumers have, of not being able to reach a far away destination due to the limited capacity of an EV battery, can be alleviated by making fast charging points available along long distance routes. However, one must differentiate between the usage of "stop-and-go" and "destination charging", the latter of which is the more common use case (Globisch et al., 2019). Long distance travel often utilises "stop-and-go" charging, where EV owners stop en route to their final destination to recharge their battery before continuing their journey (Morrissey, Weldon, and O'Mahony, 2016). Consumers often feel that charging time is an issue, especially in this use-case (Kurani, Caperello, and Tyree-Hageman, 2016), and as such the utilisation of DCFCs for these locations of "stop-and-go" charging such as along highways provides extra benefit, as it mitigates the effective range anxiety (B. Zhang et al., 2021). The more common use-case however is "destination charging", where consumers charge their EV at their travel destination for a longer period of time; usually at home or at work (Globisch et al., 2019). Here, AC charging is still clearly more beneficial once charging time is not a point of concern, as charging points are cheaper and the strain on the battery is lower for AC charging. In more urban environments, where consumers do not have the space to park vehicles on their privately owned property and have to park on public roads (Cao and Menendez, 2015), public AC chargers are still a critically lacking infrastructure as they are the only available type of "destination charger" (Porru et al., 2020). These two points can be summarised as follows: in cities with shorter travel distance and longer parking times, AC "destination chargers" are required to cover the most common uses cases. On the other hand, long range travel, usually outside of cities, requires "stop-and-go" charging points to minimise charging time thus making DC charging points far more appealing to consumers.

Lastly, some smaller technical factors also contribute towards the charging problem. The first issue being the limitations of on-board power converters in EVs. In a traditional AC charging system, the AC power outputted by the charging point, is converted to a DC current used to charge the vehicle's battery. The amount of power that can be converted from AC to DC is limited by the size of the electrical converter, with high power fast charging (at roughly 8kW) the AC to DC converters size is inhibitively large to be an on-board component of the vehicle and as such the AC to DC conversion process for fast charging must occur outside of the vehicle (Chakraborty et al., 2019). This inability to use the on-board converter for high power fast charging in EVs is one of the factors that increases the installation cost of DCFCs (Hardman et al., 2018), since the charging point needs to enclose a high power AC to DC converter to convert the mains AC power to a DC current that charges the vehicle battery. This technical limitation, beyond just the added costs associated with higher power equipment is why the costs of DCFCs are far higher than their AC counterparts and are less frequently used for public charging stations (Nelder and Rogers, 2019; Hardman et al., 2018). Beyond the charging hardware, the battery also indirectly has an effect on the usage of charging, especially in relation to DC fast charging. The first concerns most potential EV buyers cite is the "range anxiety" (Kurani, Caperello, and Tyree-Hageman, 2016), due to the battery capacity not being large enough for a long distance trip without recharging. Therefore, the capacity of battery, and the range of EVs inherently determine the design parameters for a fast charging network, with more frequent DCFC locations being required in order to compensate for low battery capacity vehicles. However, excessive usage of fast charging systems also leads to a higher amount of capacity degradation in EV batteries, which becomes an issue for consumers who wish to not unnecessarily strain their EV's battery (Björnsson and Karlsson, 2015). Ultimately, the only solution is to improve all systems involved; improving battery capacity to decrease range anxiety, increasing the DC charging network to mitigate the effects of range anxiety and increase the AC charging network so that consumers can charge their EV without putting excessive strain on their batteries.

3 Design Goal and Scope

3.1 Research Questions

Having identified the problem of an insufficient charging infrastructure, as well as the effect this has on EV market share, the goal and scope of this thesis need to be clearly defined to determine the research question, as well as the methodology used to answer the stated problem. To begin with, the scope of this research will be focused on a model of central Turin's EV charging network. Furthermore, the scope of the research will consider the effects of areas with partial access to an EV charger, however due to the low travel distance of the urban area being considered only AC chargers will be taken into consideration with DC chargers being excluded. With this scope defined, the goal of this thesis is to find an optimised improvement to the EV charging network of the determined area. In this case, the optimal improvement was formulated by a model defining the most cost effective upgrades to the charging infrastructure network, by minimising cost and while still increasing area that has access to an EV charger, ultimately maximising the cost efficiency of the future upgrades to the EV charging network. As such, a series of questions that this thesis aims to answer are found below.

In this thesis the following research question will be examined:

How can an extension to the current EV charging network of Turin be designed to maximise the cost effectiveness while providing additional utilities to consumers?

There are four sub questions being derived from the main research question that this thesis aims to answer:

1. What are common ways to improve EV charging networks and how are can they be modeled?
2. How are models adapted specifically to cities as opposed to other geographical areas?
3. How can the city of Turin's EV charging network be modeled to optimise the cost effectiveness of new infrastructure?
4. How can the optimisation model for the city of Turin be altered for future expansion scenarios?

3.2 Methodology Selection

3.2.1 Solutions to the Charging Problem

The cyclical problem involving EV charging infrastructure is not an easy one to overcome. Ultimately, the only solution to break the cycle of limited EV adoption by consumers is a significant amount of investments into EV charging infrastructure. A case study can be made from the country of Norway, where government started incentivising EV adoption since 1990. Investments in an infrastructure of 1800 chargers began in 2009 and 2010 (Lorentzen et al., 2017). Since then, Norway has greatly expanded investments in home charging, public AC and public DC fast charging, with Norway nationalising the public charging infrastructure built (Lorentzen et al., 2017). In addition to this, a public national central database of all EV charging points and a publicly available application programming interface (API) was established (Bøe, 2012). This allows businesses to easily create applications and interfaces for users to locate one of the over 19.5 thousand charging points available in the country (NOBIL, 2021), providing greater transparency and ease of use to consumers. In addition to this, the government subsidises the running cost of these charging stations to decrease the cost to consumers (Lorentzen et al., 2017). Beyond these policies solving the charging infrastructure problem, Norway has many other incentives in place for EV owners, such as exemption of a variety of vehicle related taxes on EV vehicles, access to bus lanes as well as free access to toll roads, municipal parking and ferries (Lorentzen et al., 2017). The main caveat in the case of Norway being that this aggressive strategy to push EV adoption is not replaceable by many countries, as it relies on a large disposable state income, not available on a similar scale in most countries. In the case of Norway, these large investments are financed through Norway's large state-owned petroleum and natural gas resources (Hall and Lutsey, 2017).

Most countries however, are not able or willing to fund EV charging infrastructure to the same degree as Norway. As such, more targeted strategies have emerged to selectively place a limited number of EV charging points that would see a high degree of utilisation. The Netherlands for example introduced a system where curbside EV chargers were installed in places of high usage, with additional infrastructure positioning being dependent on the usage of the existing infrastructure. Areas with high charging demands receive additional charging points (Helmus et al., 2018). Furthermore, businesses are heavily incentivised to build EV charging points on their property, under the condition that they have an employee owning an electric car that utilises the charging point (Hall and Lutsey, 2017). Beyond these systems, a number of proposals have been made by the scientific community on how to optimise the placement of EV charging points (see section 3.2.2). Often these proposals come in form of a linear programming (LP) model. These have been utilised to optimise the placement of EV charging points to minimise the impact on the energy grid (Yi and Bauer, 2016). However, these LP models are most commonly designed to either maximise the utility from public charging points or to minimise the cost of infrastructure upgrades.

3.2.2 Overview of Optimisation Methods

Optimisation models have proven a useful mathematical tool that can be used to model scheduling or allocation decision making processes (Gilmore and Gomory, 1961). As such, these types of LP models can and have already been applied to a variety of EV charging infrastructure problems. However, the models used in the past are varied in methodology and objective with a number of different goals set in form of the models objective function. Optimisation models for EV charging networks can be designed to maximise traffic flow captured (Capar et al., 2013), minimise travel time (Chen et al., 2014), maximise area coverage of charging stations (Frade et al., 2011), maximise usage of chargers (Xi, Sioshansi, and Marano, 2013), minimise the number of charging stations (J. Liu, 2012) and to minimise the network cost of an EV charger network (Lam, Leung, and Chu, 2014). For the case of this thesis, the objective was to design the most cost effective network upgrade. This was done by modelling the objective function to minimise the network upgrade cost at a variety of area coverage levels of charging stations, discussed further in the upcoming sections (4.3 and 4.4). In addition to the objective of the model, several other smaller decisions must be made. The first is the decision to model the locations as a set of area polygons or as a series of vector locations along the streets being considered. Both of these options have advantages and disadvantages, with the vector based model allowing for more accurate modeling of traffic flow (therefore allowing for prioritisation of new chargers along main roads that see more traffic flow) as well as allowing for modelling of accessibility and unidirectional flow. The polygon based approach is a simpler model allowing for a more uniform formulation of charging locations and area definition, with this approach being adopted in this thesis as traffic flow is not considered. This simpler approach was taken to serve as a baseline scenario, which can more easily be applied to future scenarios of Turin, or applied to different cities altogether, with this approach overall being easier to replicate.

After the objective of the model and the set of locations has been defined, the model must be formulated to either only consider direct coverage or to also take partial coverage into account. Here, areas considered partially covered are ones with limited access to a charging station which is less beneficial to consumers than direct access but more beneficial than no access altogether. As such, the partial coverage consideration can be introduced to evaluate more "low cost" options where the outcome is clear to not contain a charging station in every location vector or polygon. Moreover, a model considering partial coverage is a more accurate formulation of a real-world scenario, where consumers might gain utility from charging stations accessible to them but not in their direct vicinity. Additionally, a model must be designed to either consider AC charging, DC fast charging or both, as this requires some changes in the objective and constraint functions. As a more generalised rule, urban environments should primarily focus on AC charging infrastructure, whereas less urban areas associated with long distance travel should focus on DCFC infrastructure (see section 2.3). For the sake of this thesis, since the objective is to find the most cost effective solution in an urban area, a model considering AC charging exclusively while taking the partial coverage problem into consideration was determined to be the best fit.

4 Linear Programming Model

As a starting point for determining the an optimisation for the positioning of new EV charging stations, an LP optimisation model focused on the city of Turin was created using a similar model to those discussed by Huang et. al. in "The design of electric vehicle charging network" (Huang, Kanaroglou, and X. Zhang, 2016), with adjustments being made to the location set i, the partial coverage designation, the cost function and the tuning of the model to more accurately represent Turin. The first stage of building this model was gathering input data. Here, existing EV charging infrastructure locations were compiled using a geographic information system (GIS) and divided into a grid of polygons on a map as shown in figure 1. Along with other variable input parameters such as the price of building a new charging station, a target area coverage and the budget available to build new infrastructure, the model was defined. To begin with, partial coverage of specific polygons was determined by analysing an excess in charging infrastructure in adjacent polygons. Finally, the model determines if a feasible solution space is possible for the targeted coverage and determines the number and locations of EV charging stations resulting in the minimal total cost of the network, given a predetermined coverage goal.

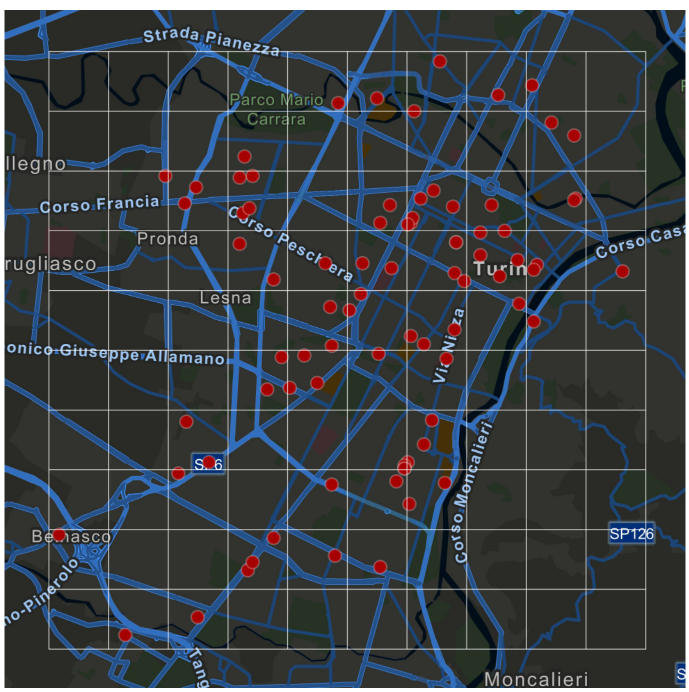

Figure 1: Existing EV charging infrastructure in Turin on a 1km^2 grid.

4.1 Installation Cost Analysis

In order to determine the total price of an improved EV charging network in the city of Turin, and to aid in overall decision making, an estimation of the price of an EV charging station must be made. Overall, the cost of a charging station depends on a number of factors. Namely, the type of charger (direct or alternating current for example), the power output that the charger is capable of and the local power network are the three factors that have the largest impact on the price (Nelder and Rogers, 2019). The model will consider an AC mode 3 charger, as this is by far the most common charging method for publicly accessible charging stations due to its cost effectiveness and moderate power consumption. According to a study performed by Nelder and Rogers, the installation cost of this type of charger ranges from $2,500 to $4,900 with power outputs ranging from 7.7 to 16.8 kW (Nelder and Rogers, 2019). A cost overview made by Nelder and Rogers, 2019 for the installation costs of AC chargers, DC fast chargers and distribution transformers can be found in figures 2, 3 and 4.

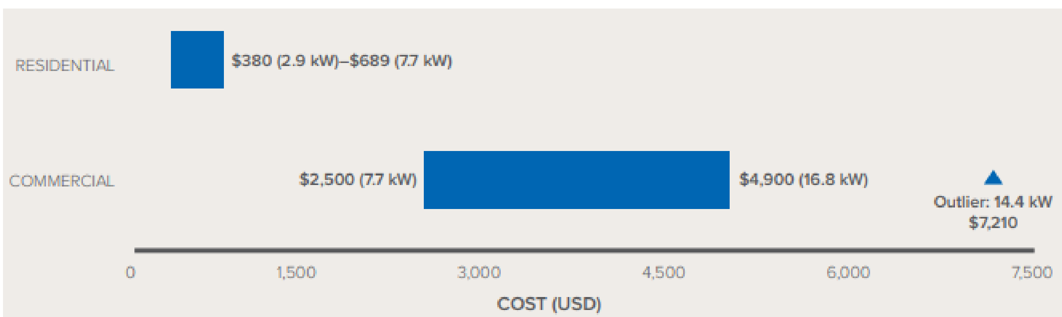

Figure 2: An overview of the range of costs associated with installing a traditional AC charger (Nelder and Rogers, 2019).

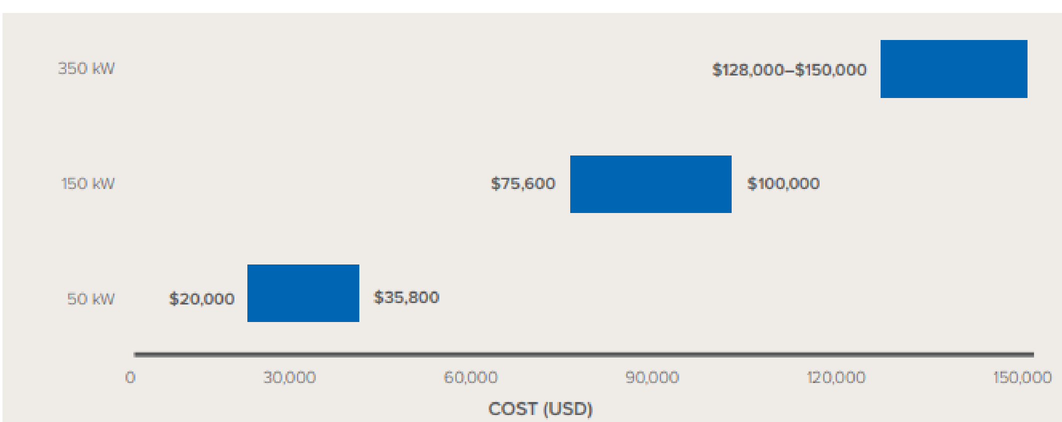

Figure 3: An overview of the range of costs associated with installing a direct current fast charger (Nelder and Rogers, 2019).

To simplify calculations, the mean values for the installation cost will be assumed to be the per-unit cost, as the total cost of an entire EV charging network can be assumed to average out when consisting of a variety of charger types and capacities. With an exchange rate of 1.18 Euro to USD (as of August 2021), a typical commercial AC powered EV charger can be assumed to be €3136. It is very important to note that this figure does not include the additional cost of upgrading existing power infrastructure. This is a large additional cost that can arise when multiple AC or a single DC fast charger (DCFC) are being installed (Nelder and Rogers, 2019). However, in most cases existing power infrastructure is sufficient to accommodate most AC and even low power DC charging infrastructure without modification (Nelder and Rogers, 2019). Higher powered DC chargers or a larger number of individual chargers could require an upgrade in the distribution transformers, resulting in additional costs ranging from €29,600 to €44,900 for smaller 150-300 kW transformers, to up to €55,900 to €146,600for top end 1000+ kW distribution (Nelder and Rogers, 2019). Due to the fact that these costs are avoided by using AC chargers, the cost of infrastructure upgrades will not be included in the model.

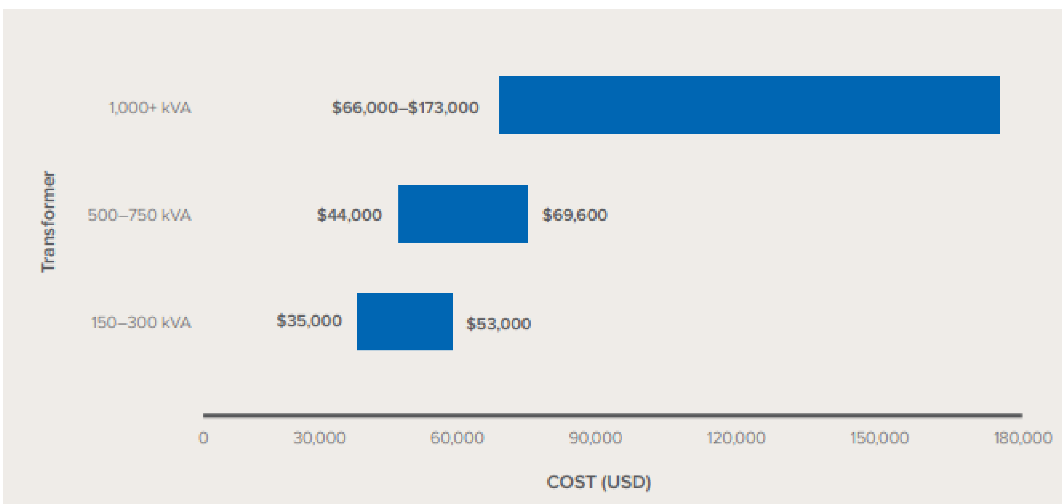

Figure 4: An overview of the range of costs associated with upgrades to distribution transformers, should these be required for new EV charging infrastructure (Nelder and Rogers, 2019).

4.2 Input Data Procurement

The most critical input for the model is the set of existing EV charging infrastructure. This data is used to determine the geographical location of the areas that are either partially or fully covered by an EV charger and therefore, which locations with low or no coverage require new charging infrastructure to be built. The most convenient source for this data is often in form of GIS data. Certain places for example the municipality Toronto, Canada, or the highway system of Korea, have a well maintained and widely available set of GIS data regarding EV charging infrastructure. As a result of this, models centred around these locations are relatively easy to create since the input data is easily accessible (Huang, Kanaroglou, and X. Zhang, 2016; Chung and Kwon, 2015). In the case of Turin however, GIS data on EV charging infrastructure is not readily available or incomplete. And as such the GIS data was put together by hand from location data from Google maps and the limited amount of location data from the municipality of Turin. For future reference, a complete GIS model put together by the author of this thesis, of existing EV charging infrastructure as of June 2021 can be found online (Lindemann, 2021). From this GIS data, the map was rasterised into one by one km and 0.5 by 0.5 km squares. The number of existing EV chargers was counted for each square to create a matrix of charging locations on the map of Turin (referred to as N in Appendix B). This data array was then reformatted to determine the area fully and partial covered by an EV charger at the current point in time, which could then be used as inputs to the model. A visual representation of this data can be found in figures 1 and 5.

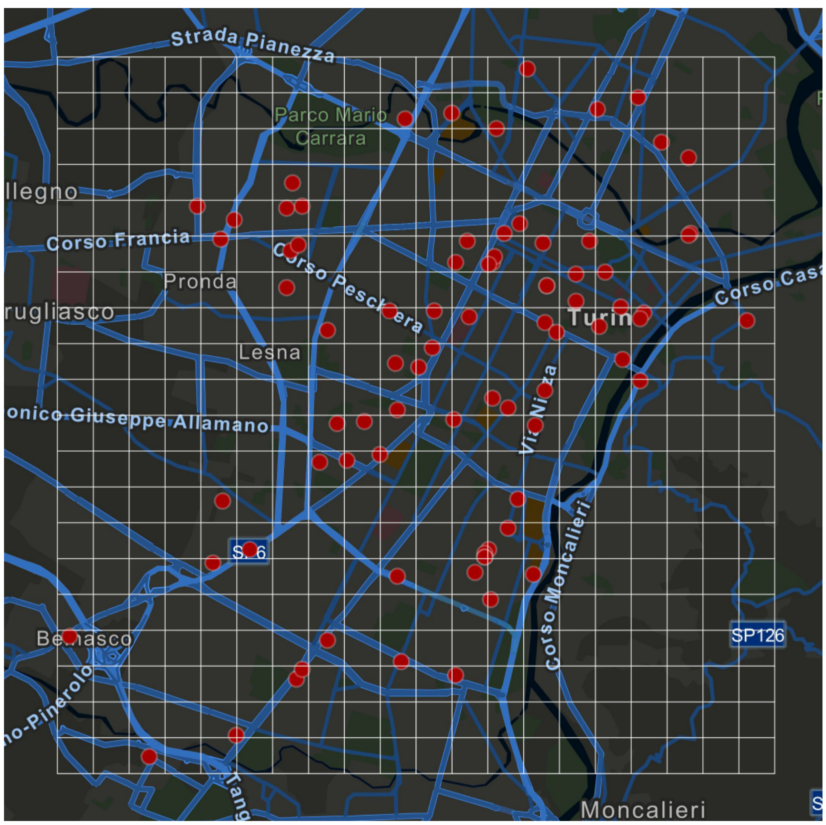

Figure 5: Existing EV charging infrastructure in Turin on a 0.25km^2 grid.

4.3 Coverage Model

Having determined location data of existing EV chargers, a number of different decision making models can be used in order to determine the optimum location of new charging stations to maximise the area covered by charging stations. Some models are highlighted by Huang, Kanaroglou, and X. Zhang, 2016, which were used as a basis for the model used in this thesis. The focus here was to create a point based decision model to minimise the number of charging stations to fulfil a coverage target using partial coverage. The model used represents the EV chargers as individual points on a map, instead of modelling them as a network of roads with charging access. Additionally it utilised the partial coverage theorem, by which areas without a charging station can be considered to have "partial access" to an EV charger if adjacent areas have sufficient EV charging infrastructure (Huang, Kanaroglou, and X. Zhang, 2016). Combined these principals were formulated into a linear programming model and then solved using Matlab (code found in Appendix B) to determine the optimal locations for new charging infrastructure. The mathematical formulation of this LP model is as follows:

Minimise:

$$\sum cx_i$$

Subject to:

$$\begin{aligned}
&y_i - x_i <= 0 \\
&\theta v_i - x_i <= 0 \\
&y_i + v_i <= 0 \\
&-\omega y_i - \beta\omega v_i <= -\alpha\omega
\end{aligned}$$

With:

i being a set of squares dividing the city of Turin, representing the location being considered.
x_i being a set of charging stations located at quadrant i.
y_i being a set of binary decision variables determining if location i is fully covered by charging stations.
v_i being a set of binary decision variables determining if location i is partially covered by charging stations.
c being the assumed constant cost to build a new charging station.

θ being the lowest coverage to be considered full coverage.
ω being the lowest coverage to be considered partial coverage.
β being the penalty coefficient used to penalise partial coverage.
α being the lowest acceptable target coverage as a percentage of area covered by a charging station.

4.4 Tuning the Model

The tuning process of selecting the correct values for specific variables has a significant effect on the output of the model, while simultaneously being quite context driven. As a result, this type of model is required to be re-tuned based on the location and use-case. For example, adjusting these variables can promote certain priorities in the output. The output could be prioritised to strongly punish partial coverage of each section, with a lower total coverage of the full area, or it could also prioritise a high total area coverage regardless of if that coverage is only partial. Ultimately, these priorities must be determined by the party building the EV charging infrastructure, and therefore must be considered before tuning the model. This section will highlight the three most important variables to tune, what there functions are within the algorithm, and how sensitive the final output is to the tuning of these variables. As a baseline scenario, the variables will be set as follows: α = 90%, β = 0.9, ω = 1, θ = 2 and i will be composed of a grid of 1 km^2 sections. This variable selection resulted in a network upgrade cost of €28,224 with nine new charging stations being added. However the implication of this figure will further be discussed in chapter 6. A visual representation of this improved EV charging network can be found in figure 6, with new charging locations being highlighted in green over the existing charging infrastructure from figure 1.

In order to adequately understand the model and the tuning process behind it, the main variables and outputs must briefly be explained. The primary goal of the model is to select a set of points x_i that represent the optimal EV charger locations, from which the number and location of new chargers and therefore the network upgrade cost can easily be derived. This output is visualised in figure 6, representing the existing chargers (model input) as red dots, and the location areas for new chargers (output of $x_i - existing\ chargers$) as green squares. For the tuning process specifically, the outputs of the model can be compared in tables 1, 2 and 3. This was done for the sake of simplicity to make an easier comparison between the proposed charging networks. However all of the networks highlighted by sections 4.4 and 6 can be found in appendix A, with the full location data for all new charging infrastructure being found there.

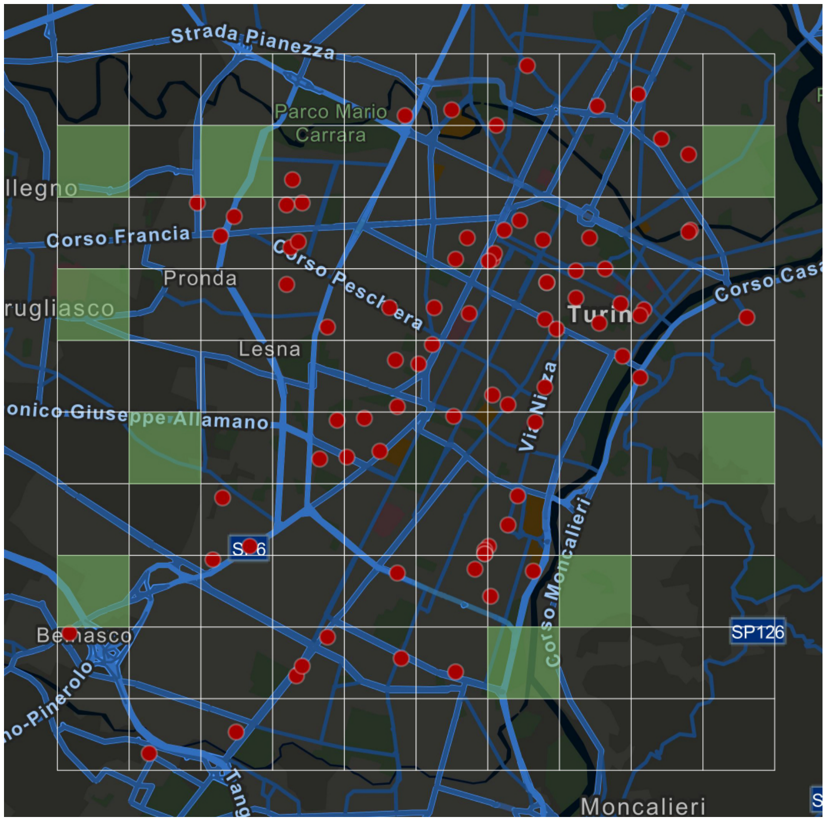

Figure 6: A preliminary selection for possible locations of new EV charging infrastructure in Turin on a 1km^2 grid based on the baseline tuning parameters.

Having introduced the output, two brief introduction must be made before the selection of the tuning variables. The first is the selection of a percentage coverage target (α value). This will essentially be the main point of consideration once a network is tuned and will be the main factor for stakeholders to consider when deciding how to upgrade the EV charging network of a given city. The effect of the alpha variable as well as a number of possible networks will be discussed in the results section (6), However as previously mentioned for the sake of tuning the model, the alpha value will be considered a controlled variable in all cases and set to 90%.

The second, and slightly more convoluted decision is the grid size, and therefore the size of the set i. Two grid sizes can be seen throughout this thesis with figure 1 showing a grind of Turin (i) composed of 1 km^2 quadrants and figure 5 composed of quadrants with half the length and width 0.25 km^2. When selecting an adequate polygon size for the i set (in this case quadrants, but other divisions can be used too), it is important to select the right size of polygon. A set of i divided into too large sections, will result in imprecise location data of the final output, as well as resulting in a large cluster of new charging locations (i.e. the model will determine that roughly 5 new charging stations need to be built in a large area which is imprecise and has limited use). Furthermore, if the length or width of a point within i exceeds the maximum walking distance an EV owner is willing to travel between a charger and their true destination, then the model output does not solve the true use case problem. This is because more charging stations will be available in a given area, but EV users often do not gain any utility from the new chargers if their destination is too far from one of these chargers. From here, it can be concluded that at minimum, the size of a polygon point within i should be such that this minimum walking distance covers the extent of that polygon. For the sake of this thesis a walking speed of 4.8 km/h (Aspelin, 2005) will be considered with maximum walking time between EV charger and destination of 20 minutes, resulting in a maximum walking distance of 1.6 km, thus even the larger 1 km^2 quadrants diagonal distance (1.41 km) is covered by this maximum. Despite this, a smaller polygon (and therefore larger set of i at a higher resolution) is not universally favourable either. A very detailed set of i might determine charging stations in a too precise location, which could create problems if the model determines a new location where a new EV charger cannot be built due to existing infrastructure for example. As a result, the resolution must be sufficiently lowered to minimise the risk of compatibility issues occurring from the models proposal of infeasible locations. Additionally, a larger set of i with more values can lead to excessive run time of the program which can prove problematic as well if analysing more complex data sets. In the case of this thesis, the lower resolution 1 km^2 quadrants were found to fulfil the minimum walking distance requirements, while the higher resolution 0.25 km^2 quadrants created run time errors in certain tuning configurations. As such the tuning process and and final results were all based on a set of i of 1 km^2 quadrants as shown in figure 1.

The final part of this section will be dedicated to explaining the significance of the three tuning variables (omega, theta and beta), as well as elaborating on their impact on the model output. The first tuning variable omega (ω) represents the minimum number of charging stations accessible by point i, for this point to be considered "partially covered" by EV chargers. Depending on the construction of the model, this can mean that point i must contain at least ω chargers to be considered partially covered, or in the case of this model it means that point i and points adjacent and accessible to i contain at least ω EV chargers for i to be considered partially covered. Table 1 shows the effect that omega has on the output of the model, with omega ranging from 1 (only one charger required for partial coverage) to 5 (five accessible chargers required for partial coverage condition). These results show, that a stricter partial coverage can lead to a shift in the model towards full coverage conditions and therefore a less effective output with lower coverage and fewer chargers added. It is recommended to select a low omega value (of 1 or 2) to effectively utilise the network efficiency advantage that partial coverage offers, however if the polygon size of i is larger, then a larger omega value should be selected. Additionally, the partial coverage condition (ω) must strictly be lower that the full coverage condition (θ), otherwise the model will not utilise partial coverage and only prioritise full coverage (since this condition is easier met) which is a similar reason why a change in the partial coverage penalty factor (β) directly affects how sensitive the output is to the omega value.

Omega Value	Network Upgrade Cost (€)	Chargers Added
1	28,224.00	9
2	21,952.00	7
3	18,123.00	6
4	12,544.00	4
5	6,272.00	2

Table 1: Effect of a tuned omega value on the output of the model.

Beyond the partial coverage condition, a value for the full coverage condition variable theta (θ) must be determined. Similar to omega, the variable theta represents the minimum number of charging stations accessible by point i, for this point to be considered "fully covered" by EV chargers. Similar to other tuning variables, the theta value must be chosen while also giving consideration to other variables such as the grid size of i, and the value set for omega. In a model considering only full coverage (i.e. $\beta = 0$ or $\theta < \omega$), the tuning of theta will be proportional to the target coverage percentage (alpha) where increasing theta by a factor of x will have a similar effect to an increase in alpha by a factor of x. However, since this model does take partial coverage into consideration, this one-to-one relationship between alpha and theta cannot be found (see tables 2 and 4). From table 2 the effect that theta has on the output of the model can be observed. As can be expected, with the model designed to punish partial coverage to incentivise full coverage, the impact that the full coverage condition (theta) has is greater than the impact of the partial coverage condition (omega). The degree to which theta is more impactful than omega is determined by the penalisation factor (beta).

Theta Value	Network Upgrade Cost (€)	Chargers Added
1	12,544.00	4
2	28,224.00	9
3	56,448.00	18
4	72,128.00	23
5	116,032.00	37

Table 2: Effect of a tuned theta value on the output of the model.

The final tuning variable beta (β) is, in effect used to "penalise" the model for only partially covering areas with charging stations, as opposed to fully covering the area with charging stations. With the Beta value ranging between zero and one, with one meaning "no penalisation" as in that partial coverage is treated equally to full coverage, and with zero effectively meaning "full penalisation" as in the model attributes zero benefit to partially covered sections. Table 3 shows the sensitivity that the final output has to an adjusted beta value. It can be recommended to select a beta value close to, but below one in order to penalise partial coverage while simultaneously utilising partial coverage as a method of reducing overall cost of the network upgrade. Ultimately, the choice of a beta value is the most impactful on the outcome of the model of the tuning variables. Not only does beta in isolation affect the output, it also determines the sensitivity the output has to both theta and omega. A small decrease in beta will therefore cause a relatively large shift in the output by more strongly prioritising full coverage over partial coverage thus increasing the number of chargers. It is usually not necessary to set beta to a value below 0.5, since this already sets most covered points to full coverage with little partial coverage (see appendix A.4). Therefore, if one wants to achieve an even stronger bias towards full coverage a simpler model without a partial coverage condition should be used, not requiring beta or omega tuning.

Beta Value	**Network Upgrade Cost (€)**	**Chargers Added**
1	21,952.00	7
0.9	28,224.00	9
0.8	65,856.00	21
0.7	90,944.00	29
0.6	97,216.00	31
0.5	103,488.00	33

Table 3: Effect of a tuned beta value on the output of the model.

5 Demand and Supply Side Extensions of the Model

After reviewing the results obtained by the model, it is important to highlight the strengths and drawbacks of it. As discussed in chapter 4, the model used was a linear programming model to solve the partial coverage problem and is therefore based on the area coverage of EV charging stations and the density of charging stations. However, when selecting the location for future charging stations, more factors need to be considered. This chapter will therefore highlight the factors not included in the model that are relevant to this decision making process in more long-term scenarios, and how these factors can be used to supplement the model to provide a clearer overall picture. This will be done by discussing the simplifications and assumptions made in the model and the effects these have. Additionally, potential alterations and extentions to the model will be highlighted and evaluated, that ultimately were not included in this thesis but should be include in future iterations of the model, as the number of EVs increase and the EV charging network is expanded further.

5.1 Supply Side Extension of the Model

The model can be split into two sections, namely an analysis of the supply of EV charging infrastructure and the demand for this infrastructure with the model attempting to find a network with an adequate supply to match consumer demand. On the supply side of this model, certain simplifications were made that could be expanded upon in future iterations which will be discussed in this section. To begin with, the model only considers AC charging infrastructure and not "fast charging" DC infrastructure. This was a deliberate choice as the main use for AC chargers are covered by the two common use cases in cities of charging an EV while at home and charging an EV while at work, both of which are associated with longer wait times meaning charge time becomes less of an issue (Globisch et al., 2019). Additionally, of course the AC chargers are far more cost effective than DC chargers, as such when a consumer is indifferent to the type of charger a supplier should focus on AC charging to reduce the infrastructure cost. Furthermore, the alpha, omega and theta values were tuned to a degree where power infrastructure investments on top of the charger installation cost was not necessary to take into account, since the upgrades necessary to the current charging infrastructure do not require additional distribution transformers (as discussed in section 4.1). Due to this, the model used could consider the cost of charging infrastructure to be constant (Nelder and Rogers, 2019). However, if either DC chargers or a higher area density of AC chargers is considered (both of which would be the case in future scenarios), then the model would have to shift from a static to a dynamic cost variable. Once this dynamic cost variable is established, the model is designed in a way such that only the objective function would have to be altered to minimise $\sum c_i x_i$, with c becoming the dynamic cost of installing a charging station at location i, similar to Ge, Feng, and H. Liu, 2011.

For the case of Turin, this cost variable would have to be determined in collaboration with a 3rd party. This is due to the fact that the back end power infrastructure is not of public record, and therefore the requirement of additional distribution transformer placement cannot be determined (required for multiple AC or a single DC charger). This information would have to be obtained either from the power companies directly or through a local government organisation such as the Osservatorio Energia of the City of Turin (Cittametropolitana di Torino, n.d.) or the regulatory authority for the energy network and environment ARERA (ARERA, n.d.). Ultimately, the main issue in finding this data is the small scale required for the model to work on, however estimations could also be made for larger areas (i.e. the installation cost in district x is cx and the cost in district y is cy). This coarse cost estimation could be used if a permutation of the model is created that requires a dynamic cost variable. Additionally, the cost variable could be altered to only consider the number of stations created and not the geographic cost difference. Here the cost of one AC charger would be considered as €3136 (found in section 4.1), and the cost of a high number of AC chargers (n) would be €3136*n + the cost to the distribution transformer (with a similar cost calculation for DC chargers).

5.2 Demand Side Extension of the Model

In addition to the supply side of these EV chargers, the demand side and the use pattern of the charging network can be further analysed as well. Consumers state that the two most frequent places they would charge an EV is at home and at work (Hardman et al., 2018). This means that potential charging stations in an area of high residential population density and a high working population density are of greater importance. Similarly to the previous section (5.1), location data on such a small scale is difficult to obtain without additional primary research. Again, the exact location data could be substituted with data from individual city districts (with the assumption of even population distribution over that district), which is more readily available from the local city authority which in the case of Turin would be the statistics office of the local commune (Comune di Torino, n.d.). A similar approach could be taken to obtain the quantitative data on the work location of consumers. Another method used by infrastructure providers is to monitor demand along existing charging points to extrapolate demand to future charging point locations.

Once obtained, this data could be used to prioritise infrastructure spendings to favour high population (and therefore high demand) areas. This could be done to sort the model output variable (x_i into areas of high demand (categorised by subsections of i) and areas of lower demand. If this approach is chosen, it can be recommended to categorise these subsections of i by both number of residents and number of people working within these locations in i, since often areas of cities can be categorised as mainly residential or mainly industrial/commercial areas. Only if both of these categories are included can the main two use cases be considered covered in the prioritisation model. However, if additional actions are taken, such as subsidising private businesses to install their own EV chargers for employees, then one of the two categorisations can be ignored assuming the use case is covered elsewhere, through non-public infrastructure for example.

6 Results

One of the major problems in the EV market has been the lack of charging infrastructure and the lowered consumer interest that results from this. It is therefore crucial to alleviate this causality problem by carefully analysing the output that the linear programming model provides. Having tuned set up this model specifically for the city of Turin, and with the variable tuning process completed one must consider how new EV chargers can be added to the existing infrastructure in the most cost effective manner. For this cost to performance consideration, both the area percentage covered by EV charging infrastructure (alpha), as well as the network upgrade cost (the sum of installation cost of all newly proposed charging infrastructure) were considered. With regard to the city of Turin, these cost to performance indicators can be found in table 4. It can be seen that a number of upgrades can be made to the charging infrastructure. At the time of writing, the existing charging infrastructure (found in figure 1) covers only 62% of the area of central Turin. With the proposals made, the most cost effective upgrade in terms of coverage percentage increase per Euro would be to add 7 EV chargers to the network at a cost of €21,952 (85% area coverage). This would result in a cost efficiency of 954.43 Euros per percent increase in coverage, with a close second of 1,008.00 euro per percentage resulting from the scenario of increasing area coverage to 90%.

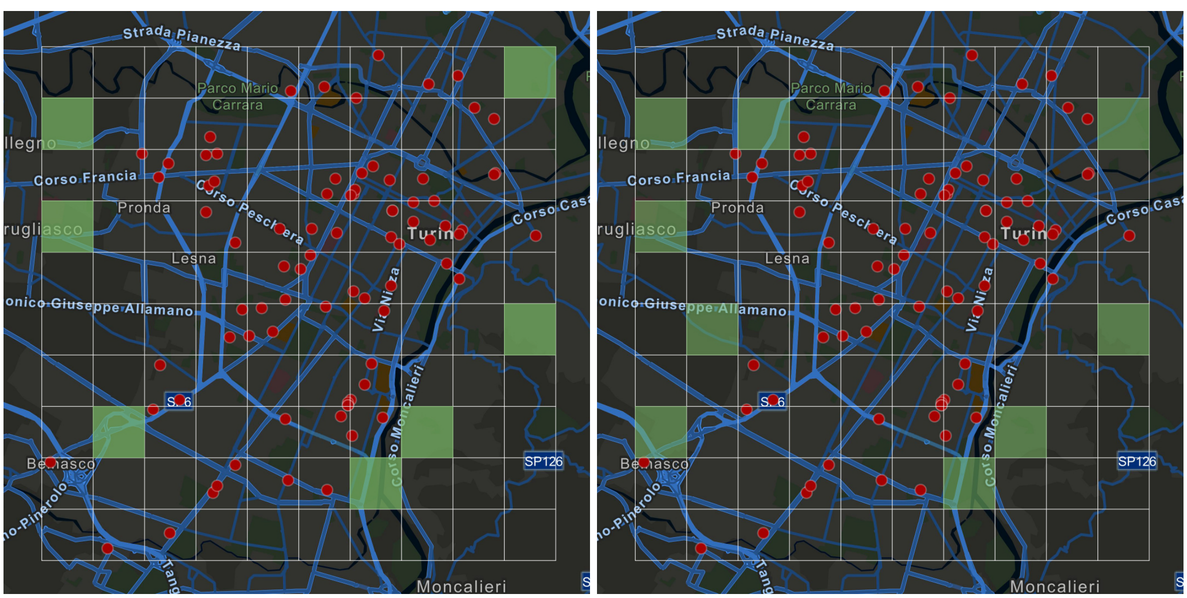

Figure 7: A map of the new EV charging locations for the both scenarios of 85% area coverage (left) and 90% area coverage (right)

Percentage coverage α	**Network Upgrade Cost (€)**	**Chargers Added**
80%	18,816.00	6
85%	21,952.00	7
90%	28,224.00	9
95%	65,856.00	21
99%	116,032.00	37
99.9%	128,576.00	41

Table 4: The installation cost of an upgraded EV charging network in the city of Turin for a number of different coverage targets (alpha)

Considering these results, two network upgrades can be proposed to stakeholders responsible for infrastructure upgrades: firstly, a frugal upgrade to 85% coverage costing a total of roughly €22 thousand, or a slightly more performance oriented upgrade to 90% coverage costing roughly €28 thousand as can be seen in figure 7. For the sake of this thesis, it is recommended to opt for the 90% coverage option if possible, as this is a coverage target found to be effective by other scientific papers (Huang, Kanaroglou, and X. Zhang, 2016) and in the case of Turin it is the second most cost effective coverage target in terms of percentage coverage gain per euro spent. Considering this upgrade cost is within the range of a low-end 50 kW DC fast charger (Nelder and Rogers, 2019), it can also be concluded that a network upgrade for a city centre costing as much as a single fast charging station not including transformer upgrade costs is both feasible for stakeholders to invest in and within their interest.

7 Conclusion and Evaluation

7.1 Conclusion

Overall, the desired outcome of proposing a cheap and cost-effective upgrade plan for the EV charging network in Turin was achieved. The network achieving 90% target coverage described in section 6 is clearly an effective upgrade to the network at a relatively low cost of €28,224. Comparatively, estimated EV charging network upgrade costs for other Italian cities on the island of Sardinia are estimated to be in the hundreds of thousands euro range (Porru et al., 2020), however these two figures are not quite comparable since future additions to the charging network in Turin would of course add additional costs beyond the €28,224. From here, it is reasonable to strongly recommend to the municipality of Turin to invest into these new charging stations, as it is far more cost effective than plans for other cities while simultaneously making EV ownership more attractive for Turin residents, a strategy that has proven successful for places such as Norway (as discussed in section 3.2.1). Should public institutions not be interested in pursuing this investment strategy, private institutions could be convinced to invest the €28,224 to gain a strong foothold in the EV charging market of Turin. Since the investment is relatively small, and early adoption of EV owners of one public EV charging supplier over another could prove to be very lucrative in gaining long-term market share, this infrastructure investment could be also be seen as worthwhile for private sector firms too.

It is at this point critical to state that this €28,224 investment into public charging infrastructure should be considered a first step into building EV charging infrastructure. For widespread adoption of EV far more chargers must be built and made accessible to the public, along with strong additional benefits to EV owners in the city (Bonges and Lusk, 2016). This could be done by giving EV owners increased and/or cheaper access to public parking within the city of Turin, as well as additional benefits such as greater access to the restricted traffic area in the centre of Turin (ZTL) for EV drivers that are not available to privately owned ICE vehicles. In addition to this AC charging infrastructure, DCFC infrastructure needs to be added in the long run to allow Turin residents better access to surrounding areas that would otherwise be more limited for EV owners to access.

Considering that additional EV charging infrastructure planning will be required in the future, the key alterations to be model will again be highlighted here, should stakeholders decide to utilise another coverage based model. It is unfortunate that a "one size fits all" model, even for a specific city is not feasible and therefore a new and adjusted model would be required. For the city of Turin itself, since most travel is likely to be achievable on one EV battery charge, a scaled model with the higher demand requirements of a larger population of EV owners could be achieved by a simple re-tune of both the partial and full coverage requirement parameter (omega and theta). Beyond planning for the future demand increase, one could also tighten the usage requirements in conjunction with the previous re-tuning changes by decreasing the walking distance of EV owners to and from chargers. This could be achieved by increasing the resolution of the area covered by the set i (as seen in figure 5) and/or increasing the coverage target (alpha). As previously mentioned however, one must not select a too high resolution of i as a precise location that the model determines to be optimal for a new charging station is more likely to not be feasible, due to existing building infrastructure.

Further in the future, once the coverage of charging infrastructure is deemed sufficient for current or near-future demand, the implementation of DC fast chargers infrastructure in additional to AC chargers, as well as areas outside of the city, such as connections to other regional destinations or highway connections to other cities must be considered as well. In order for models to account for DCFCs, an additional decision variable similar to x_i must be introduced to define the existence of a DCFC at location i. This new variable would require an adjustment to both the objective function and the set of constraint inequalities if the model requires both DCFCs and AC chargers to be considered in the same area. When only considering a non-urban area such as the highway connection between multiple cities, it would be possible to only consider DCFCs and forgo including AC charging all together, greatly simplifying the model. Furthermore, the set of i would have to be reworked to include the new areas being considered. Further considerations, such as changing i from a point to a vector format (as described in section 3.2.2), or building the model without the consideration of partial coverage, should be reconsidered at this point as well, as these decisions both have benefits and drawbacks that should be evaluated on a case-by-case basis.

7.2 Evaluation

Although this form of LP model can be used to accurately model potential upgrades to Turin's EV charging network in the short term, it is not without flaws. As previously mentioned, it is impossible to have a "one size fits all" style optimisation model. As such the model and the resulting proposed upgrades are an accurate estimation of current conditions and demand for the city of Turin, with more long-term planning and re-tuning of the LP model being required as EV ownership increases. The main cause of this is the variability within the tuning process, with small changes in the tuning variables having a significant effect on the output of the model. Therefore, requiring LP models analysing different geographical locations to be fully re-tuned or even use a different model all together. With the selection of these tuning variables being highly context driven, even requiring re-tuning over time, the model can only be used to analyse and optimise a static point in time, rather than analysing the charging network dynamically as new infrastructure is built bit by bit. Furthermore, a model considering both AC and DCFC would have to be considered in the long run which would again require a significant reworking of the model (see section 7.1).

Beyond these inflexibilities in using the model for different locations or points in time, some static variables could prove problematic in the future (as mentioned in sections 5.1 and 5.2). With future iterations of the model that consider DCFCs or an area dense placement of AC chargers, the power infrastructure can prove to be a limiting factor (Nelder and Rogers, 2019). For this scenario to be accurately reflected in the model, a dynamic installation cost function would have to be defined, as installation cost could be area dependant with specific locations requiring upgrades to the distribution transformers. Additionally, as the area of the model increases there inherently will be a larger discrepancy in the demand for EV chagrers. While the assumption of equal demand distribution is not uncommon (Huang, Kanaroglou, and X. Zhang, 2016), a larger area containing both urban and more rural districts, the distribution of housing and places of work becomes less homogeneous than in a city centre. As such, areas with a high residential population and areas with a high amount of work places will see a higher demand for EV charging than other areas, thus requiring a dynamic approach to modelling the demand for EV chargers. In both of these cases (dynamic demand model and dynamic cost model) the LP model would require re-tuning and alterations to the objective function at minimum, beyond the additional data gathering required to accurately model the new demand and installation cost functions.

References

Adepetu, Adedamola and Srinivasan Keshav (2017). “The relative importance of price and driving range on electric vehicle adoption: Los Angeles case study”. In: *Transportation* 44.2, pp. 353–373.

Ajanovic, Amela and Reinhard Haas (2018). “Electric vehicles: solution or new problem?” In: *Environment, Development and Sustainability* 20.1, pp. 7–22.

ARERA (n.d.). *Dati Statistici*. URL: https://www.arera.it/it/dati/elenco_dati.htm.

Aspelin, Karen (2005). *Establishing Pedestrian Walking Speeds*. URL: https://www.westernite.org/datacollectionfund/2005/psu_ped_summary.pdf.

Björnsson, Lars-Henrik and Sten Karlsson (2015). “Plug-in hybrid electric vehicles: How individual movement patterns affect battery requirements, the potential to replace conventional fuels, and economic viability”. In: *Applied Energy* 143, pp. 336–347. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2015.01.041. URL: https://www.sciencedirect.com/science/article/pii/S0306261915000471.

Bøe, Vegard (2012). *Welcome to the charging Station DATABASE NOBIL*. URL: https://info.nobil.no/eng.

Bonges, Henry A. and Anne C. Lusk (2016). “Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation”. In: *Transportation Research Part A: Policy and Practice* 83, pp. 63–73. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2015.09.011. URL: https://www.sciencedirect.com/science/article/pii/S0965856415002451.

Cao, Jin and Monica Menendez (2015). “System dynamics of urban traffic based on its parking-related-states”. In: *Transportation Research Part B: Methodological* 81. ISTTT 21 for the year 2015, pp. 718–736. ISSN: 0191-2615. DOI: https://doi.org/10.1016/j.trb.2015.07.018. URL: https://www.sciencedirect.com/science/article/pii/S0191261515001654.

Capar, Ismail, Michael Kuby, V. Jorge Leon, and Yu-Jiun Tsai (2013). “An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations”. In: *European Journal of Operational Research* 227.1, pp. 142–151. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2012.11.033. URL: https://www.sciencedirect.com/science/article/pii/S0377221712008855.

Chakraborty, Sajib, Hai-Nam Vu, Mohammed Mahedi Hasan, Dai-Duong Tran, Mohamed El Baghdadi, and Omar Hegazy (2019). “DC-DC converter topologies for electric vehicles, plug-in hybrid electric vehicles and fast charging stations: State of the art and future trends”. In: *Energies* 12.8, p. 1569.

Chen, Nan, Lauren M Gardner, Melissa Duell, and S Travis Waller (2014). “Evaluating Location Alternatives for Electric Vehicle Re-charging Infrastructure Using a Distance Constrained Equilibrium Assignment Model”. In: *Transportation Research Board 93rd Annual Meeting*. 14-1840.

Chung, Sung Hoon and Changhyun Kwon (2015). “Multi-period planning for electric car charging station locations: A case of Korean Expressways”. In: *European Journal of Operational Research* 242.2, pp. 677–687. ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2014.10.029. URL: https://www.sciencedirect.com/science/article/pii/S0377221714008509.

Cittametropolitana di Torino, CSI (n.d.). *Cittàmetropolitana di Torino*. URL: http://www.cittametropolitana.torino.it/cms/ambiente/risorse-energetiche/osservatorio-energia.

Comune di Torino, Citta di Torino (n.d.). *Dati Statistici*. URL: http://www.comune.torino.it/statistica/dati/territ.htm.

Concha, Gabriela, Karin Broberg, Margaretha Grandér, Alejandro Cardozo, Brita Palm, and Marie Vahter (2010). “High-level exposure to lithium, boron, cesium, and arsenic via drinking water in the Andes of northern Argentina”. In: *Environmental science & technology* 44.17, pp. 6875–6880.

Coren, Michael J. (Aug. 2019). *The median electric car in the US is getting cheaper*. URL: https://qz.com/1695602/the-average-electric-vehicle-is-getting-cheaper-in-the-us/.

Danielis, Romeo, Lucia Rotaris, Marco Giansoldati, and Mariangela Scorrano (2020). “Drivers' preferences for electric cars in Italy. Evidence from a country with limited but growing electric car uptake”. In: *Transportation Research Part A: Policy and Practice* 137, pp. 79–94. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2020.04.004. URL: https://www.sciencedirect.com/science/article/pii/S0965856420305590.

Davis, River and Tsuyoshi Inajima (June 2021). *It's Too Early to Focus on Electric Cars Only, Toyota Says*. URL: https://www.bloomberg.com/news/articles/2021-06-16/it-s-too-early-to-focus-on-electric-cars-only-toyota-says.

Dunn, Jennifer B, Linda Gaines, John Sullivan, and Michael Q Wang (2012). “Impact of recycling on cradle-to-gate energy consumption and greenhouse gas emissions of automotive lithium-ion batteries”. In: *Environmental science & technology* 46.22, pp. 12704–12710.

Faria, Ricardo, Pedro Marques, Pedro Moura, Fausto Freire, Joaquim Delgado, and Anıbal T De Almeida (2013). “Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles”. In: *Renewable and Sustainable Energy Reviews* 24, pp. 271–287.

Faria, Ricardo, Pedro Moura, Joaquim Delgado, and Anibal T De Almeida (2012). “A sustainability assessment of electric vehicles as a personal mobility system”. In: *Energy Conversion and Management* 61, pp. 19–30.

Frade, Inês, Anabela Ribeiro, Gonçalo Gonçalves, and António Pais Antunes (2011). “Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal”. In: *Transportation Research Record* 2252.1, pp. 91–98. DOI: 10.3141/2252-12. eprint: https://doi.org/10.3141/2252-12. URL: https://doi.org/10.3141/2252-12.

Ge, Shaoyun, Liang Feng, and Hong Liu (2011). "The planning of electric vehicle charging station based on Grid partition method". In: *2011 International Conference on Electrical and Control Engineering*, pp. 2726–2730. DOI: 10.1109/ICECENG.2011.6057636.

Gilmore, Paul and Ralph Gomory (1961). "A linear programming approach to the cutting-stock problem". In: *Operations research* 9.6, pp. 849–859.

Globisch, Joachim, Patrick Plötz, Elisabeth Dütschke, and Martin Wietschel (2019). "Consumer preferences for public charging infrastructure for electric vehicles". In: *Transport Policy* 81, pp. 54–63. ISSN: 0967-070X. DOI: https://doi.org/10.1016/j.tranpol.2019.05.017. URL: https://www.sciencedirect.com/science/article/pii/S0967070X1830742X.

Hall, Dale and Nic Lutsey (2017). "Emerging best practices for electric vehicle charging infrastructure". In: *Washington, DC: The International Council on Clean Transportation (ICCT)*.

Hardman, Scott, Alan Jennand, Gil Tal, Jonn Axsen, George Beard, Nicolo Daina, Erik Figenbaum, Niklas Jakobsson, Patrick Jochem, Neale Kinnear, Patrick Plötz, Jose Pontes, Nazir Refa, Frances Sprei, Tom Turrentine, and Bert Witkamp (2018). "A review of consumer preferences of and interactions with electric vehicle charging infrastructure". In: *Transportation Research Part D: Transport and Environment* 62, pp. 508–523. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2018.04.002. URL: https://www.sciencedirect.com/science/article/pii/S1361920918301330.

Hawkins, Andrew J. (Apr. 2021). *Toyota finally gets off its ass and announces a real electric VEHICLE STRATEGY*. URL: https://www.theverge.com/2021/4/19/22391738/toyota-electric-vehicle-strategy-bz4x-concept-subaru.

Helmus, J.R., J.C. Spoelstra, N. Refa, M. Lees, and R. van den Hoed (2018). "Assessment of public charging infrastructure push and pull rollout strategies: The case of the Netherlands". In: *Energy Policy* 121, pp. 35–47. ISSN: 0301-4215. DOI: https://doi.org/10.1016/j.enpol.2018.06.011. URL: https://www.sciencedirect.com/science/article/pii/S0301421518303999.

Huang, Kai, Pavlos Kanaroglou, and Xiaozhou Zhang (2016). "The design of electric vehicle charging network". In: *Transportation Research Part D: Transport and Environment* 49, pp. 1–17. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2016.08.028. URL: https://www.sciencedirect.com/science/article/pii/S1361920915300778.

ISO (2006). "ISO 14040:2006 Environmental management — Life cycle assessment — Principles and framework". In:

Kurani, Kenneth S, Nicolette Caperello, and Jennifer Tyree-Hageman (2016). "New car buyers' valuation of zero-emission vehicles: California". In:

Lam, Albert Y. S., Yiu-Wing Leung, and Xiaowen Chu (2014). "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions". In: *IEEE Transactions on Smart Grid* 5.6, pp. 2846–2856. DOI: 10.1109/TSG.2014.2344684.

Leuenberger, Marianne and Rolf Frischknecht (2010). "Life cycle assessment of battery electric vehicles and concept cars". In: *Report, ESU-Services Ltd* 2, pp. 309–314.

Lindemann, Adrian (2021). *EV Charging Stations Turin*. URL: `https://www.arcgis.com/home/webmap/viewer.html?webmap=c3f7e03e808f4d949a2550429bd757f5`.

Liu, Jian (2012). "Electric vehicle charging infrastructure assignment and power grid impacts assessment in Beijing". In: *Energy Policy* 51. Renewable Energy in China, pp. 544–557. ISSN: 0301-4215. DOI: `https://doi.org/10.1016/j.enpol.2012.08.074`. URL: `https://www.sciencedirect.com/science/article/pii/S0301421512007562`.

Lorentzen, Erik, Petter Haugneland, Christina Bu, and Espen Hauge (2017). "Charging infrastructure experiences in Norway-the worlds most advanced EV market". In: *EVS30 Symposium*, pp. 9–11.

Lyon, Peter (July 2021). *Hybrid pioneer Toyota Pushes Congress to slow Down transition to electric cars*. URL: `https://www.forbes.com/sites/peterlyon/2021/07/29/hybrid-pioneer-toyota-pushes-congress-to-slow-down-transition-to-electric-cars/`.

Meshram, Pratima, Abhilash Mishra, Rina Sahu, et al. (2020). "Environmental impact of spent lithium ion batteries and green recycling perspectives by organic acids–A review". In: *Chemosphere* 242, p. 125291.

Morrissey, Patrick, Peter Weldon, and Margaret O'Mahony (2016). "Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour". In: *Energy Policy* 89, pp. 257–270. ISSN: 0301-4215. DOI: `https://doi.org/10.1016/j.enpol.2015.12.001`. URL: `https://www.sciencedirect.com/science/article/pii/S0301421515302159`.

Nelder, Chris and Emily Rogers (2019). "Reducing EV charging infrastructure costs". In: *Rocky Mountain Institute*.

NOBIL (2021). *Statistikk fra NOBIL*. URL: `https://info.nobil.no/index.php/nyheter/89`.

Notter, Dominic A, Marcel Gauch, Rolf Widmer, Patrick Wager, Anna Stamp, Rainer Zah, and Hans-Jorg Althaus (2010). *Contribution of Li-ion batteries to the environmental impact of electric vehicles*.

Porru, Mario, Alessandro Serpi, Mario Mureddu, and Alfonso Damiano (2020). "A Multistage Design Procedure for Planning and Implementing Public Charging Infrastructures for Electric Vehicles". In: *Sustainability* 12.7, p. 2889.

Rezvani, Zeinab, Johan Jansson, and Jan Bodin (2015). "Advances in consumer electric vehicle adoption research: A review and research agenda". In: *Transportation research part D: transport and environment* 34, pp. 122–136.

Tesla (n.d.[a]). *Supercharger*. URL: `https://www.tesla.com/supercharger`.

— (n.d.[b]). *Superchargers: Frequently Asked Questions*. URL: `https://www.tesla.com/en_EU/support/supercharging`.

Toyota (Apr. 2021). *Toyota hydrogen fuel Cell ELECTRIC: Toyota Europe*. URL: `https://www.toyota-europe.com/world-of-toyota/electrified/fuel-cell/`.

Toyota (n.d.). *Global website: 75 years OF Toyota: Section 8. integrating it and exploring new energy Sources: Item 1. development of Prius and hybrid strategy*. URL: https://www.toyota-global.com/company/history_of_toyota/75years/text/leaping_forward_as_a_global_corporation/chapter4/section8/item1.html.

Toyota Magazine, UK (May 2021). *Toyota electric Car strategy - electrification across the Line-up by 2025*. URL: https://mag.toyota.co.uk/electrification-across-entire-toyota-line-up-from-2025/.

Wang, Ning, Linhao Tang, and Huizhong Pan (2017). "Effectiveness of policy incentives on electric vehicle acceptance in China: A discrete choice analysis". In: *Transportation Research Part A: Policy and Practice* 105, pp. 210–218. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2017.08.009. URL: https://www.sciencedirect.com/science/article/pii/S0965856417303099.

Wesseling, JH, J Faber, and MP Hekkert (2014). "How competitive forces sustain electric vehicle development". In: *Technological Forecasting and Social Change* 81, pp. 154–164.

Xi, Xiaomin, Ramteen Sioshansi, and Vincenzo Marano (2013). "Simulation–optimization model for location of a public electric vehicle charging infrastructure". In: *Transportation Research Part D: Transport and Environment* 22, pp. 60–69. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2013.02.014. URL: https://www.sciencedirect.com/science/article/pii/S1361920913000345.

Xiang, Yue, Hao Zhou, Wei Yang, Junyong Liu, Yi Niu, and Jiahui Guo (2017). "Scale evolution of electric vehicles: A system dynamics approach". In: *Ieee Access* 5, pp. 8859–8868.

Yi, Zonggen and Peter H. Bauer (2016). "Optimization models for placement of an energy-aware electric vehicle charging infrastructure". In: *Transportation Research Part E: Logistics and Transportation Review* 91, pp. 227–244. ISSN: 1366-5545. DOI: https://doi.org/10.1016/j.tre.2016.04.013. URL: https://www.sciencedirect.com/science/article/pii/S1366554515302520.

Zhang, Bin, Niu Niu, Hao Li, Zhaohua Wang, and Weijun He (2021). "Could fast battery charging effectively mitigate range anxiety in electric vehicle usage?Evidence from large-scale data on travel and charging in Beijing". In: *Transportation Research Part D: Transport and Environment* 95, p. 102840. ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2021.102840. URL: https://www.sciencedirect.com/science/article/pii/S1361920921001437.

A Appendix A: Raw Output Data

Please note that the following data is a square representation of the output variable x minus the input variable N. This shows the location of new charging infrastructure, with 0 representing no new infrastructure at location i, and 1 representing the location for new charging infrastructure at location i.

Variable	Baseline Value
Coverage Percentage Alpha	90%
Grid Size	$1km^2$ (n100 variable)
Beta Value	0.9
Omega Value	1
Theta Value	2

Table 5: Appendix table showing the baseline values for the tuning variables of the model.

A.1 Model Outputs From Final Results

Alpha = 80%									
0	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Alpha = 85%									
0	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Alpha = 90%									
0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Alpha = 95%									
0	0	1	1	0	0	0	0	0	1
1	0	0	0	0	1	0	0	0	1
1	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	1	0	1
0	0	0	0	1	0	0	1	0	0
1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	1	0	0	0	0

Alpha = 99%									
0	0	1	1	0	0	0	0	0	1
1	1	1	0	1	1	0	1	0	1
1	0	0	0	1	0	0	0	0	1
1	1	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	1	1	1
0	0	0	1	1	0	0	1	0	0
1	1	0	1	0	0	0	1	0	0
0	1	1	0	0	0	1	1	0	0
1	0	0	1	1	1	1	0	0	0

Alpha = 99.9%									
0	0	1	1	0	0	0	0	0	1
1	1	1	0	1	1	0	1	0	1
1	0	0	0	1	0	0	0	0	1
1	1	1	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	1
0	1	1	0	0	0	0	1	1	1
0	1	0	1	1	0	0	1	0	0
1	1	0	1	0	0	0	1	0	0
0	1	1	0	0	0	1	1	0	0
1	0	0	1	1	1	1	0	0	0

A.2 Model Outputs From Tuning Omega

Omega = 1									
0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Omega = 2									
0	0	0	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	1	0	0
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0

Omega = 3									
0	0	0	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Omega = 4									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Omega = 5									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

A.3 Model Outputs From Tuning Theta

Theta = 1									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Theta = 2									
0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Theta = 3									
0	0	1	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0	1
0	0	0	0	0	0	0	0	0	0
1	1	0	1	0	0	0	1	0	0
0	0	0	0	0	0	1	1	0	0
0	0	0	0	0	1	0	0	0	0

Theta = 4									
0	0	1	0	0	0	0	0	0	0
0	1	0	0	1	0	0	0	0	1
1	0	0	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	1	1
0	1	0	1	0	0	0	1	0	0
1	0	0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	1	0	0
1	0	0	0	1	0	1	0	0	0

Theta = 5									
0	0	1	1	0	0	0	0	0	1
1	1	1	0	1	1	0	1	0	0
0	0	0	0	1	0	0	0	0	1
1	1	0	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	1
0	1	1	0	0	0	0	1	1	1
0	1	0	1	1	0	0	1	0	0
1	1	0	1	0	0	0	1	0	0
0	1	1	0	0	0	1	0	0	0
1	0	0	1	1	1	1	0	0	0

A.4 Model Outputs From Tuning Beta

Beta = 1									
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Beta = 0.9									
0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0

Beta = 0.8									
0	0	1	1	0	0	0	0	0	1
1	0	1	0	0	1	0	1	0	1
0	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	1	0	1
0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0
1	0	0	0	0	1	1	0	0	0

Beta = 0.7									
0	0	1	0	0	0	0	0	0	1
1	0	0	0	1	1	0	1	0	1
1	0	0	0	1	0	0	0	0	1
1	1	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1
0	1	0	0	0	0	0	0	0	1
0	0	0	1	1	0	0	0	0	0
1	1	0	1	0	0	0	1	0	0
0	1	1	0	0	0	1	0	0	0
1	0	0	1	1	0	1	0	0	0

Beta = 0.6									
0	0	1	1	0	0	0	0	0	1
1	0	1	0	1	1	0	1	0	1
0	0	0	0	1	0	0	0	0	1
1	0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0
0	1	1	0	0	0	0	0	1	1
0	1	0	1	1	0	0	0	0	0
1	0	0	1	0	0	0	1	0	0
0	1	1	0	0	0	1	0	0	0
1	0	0	1	1	1	0	0	0	0

Beta = 0.5									
0	0	1	0	0	0	0	0	0	1
0	1	0	0	1	1	0	1	0	1
1	0	0	0	1	0	0	0	0	1
0	1	1	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	1
0	1	1	0	0	0	0	1	0	1
0	1	0	1	1	0	0	1	0	0
1	1	0	1	0	0	0	0	0	0
0	1	1	0	0	0	0	1	0	0
1	0	0	1	1	0	1	0	0	0

B Appendix B: Matlab Code

B.1 Variable Setup Script

```
clc
clear all

%Setting parameters
%-----------------------------------------------
%c is the constant cost of building a charging station
c = 3136;

%B is the budget allocated to install EV charging stations
B = 1000000; %relatively arbitrary value in this context but can be altered when budget is a limiting factor

%alpha is the lowest acceptable coverage percentage
alpha = 0.90;

%beta is the penalty coefficient for demand partially covered by at least h number of charging stations and not fully covered
%beta is between zero and one
beta = 0.9;

%omega is the lowest level of coverage that will be considered in complementary partial coverage
omega = 1;

```

```
%theta the lowest number of partial coverage needed to be treated as full coverage
theta = 2;

%N(i) is the set of existing charging locations

%n10 is a grid of 1km^2 squares
n100 = [0,0,0,0,1,1,1,1,1,0;
        0,0,0,1,0,0,1,0,2,0;
        0,1,2,4,0,3,5,2,2,0;
        0,0,0,2,1,2,3,4,2,1;
        0,0,0,0,2,2,3,1,1,0;
        0,0,0,2,3,1,1,0,0,0;
        0,0,2,0,0,2,3,0,0,0;
        0,0,1,0,1,1,2,0,0,0;
        1,0,0,3,1,1,0,0,0,0;
        0,1,1,0,0,0,0,0,0,0];
%n25 is a grid of 0.25 km^2 squares
n25 = [0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0;
        0,0,0,0,0,0,0,0,0,1,0,1,0,0,0,1,1,0,0,0;
        0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,1,1,0,0;
        0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0;
        0,0,0,1,1,0,2,0,0,0,0,0,2,0,0,0,0,2,0,0;
        0,0,0,0,1,0,2,0,0,0,0,3,2,1,0,1,0,0,0,0;
        0,0,0,0,0,0,1,0,0,0,0,0,0,1,2,1,0,0,0,0;
        0,0,0,0,0,0,0,1,0,1,1,1,0,2,0,1,2,0,0,1;
        0,0,0,0,0,0,0,0,0,1,2,0,0,0,0,1,0,0,0,0;
        0,0,0,0,0,0,0,0,0,1,0,0,2,1,0,0,1,0,0,0;
        0,0,0,0,0,0,0,1,1,0,0,1,0,1,0,0,0,0,0,0;
        0,0,0,0,0,0,0,1,2,0,0,0,0,0,0,0,0,0,0,0;
        0,0,0,0,1,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0;
        0,0,0,0,0,1,0,0,0,0,0,3,1,0,0,0,0,0,0,0;
        0,0,0,0,1,0,0,0,0,1,0,1,0,1,0,0,0,0,0,0;
        0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0;
        1,0,0,0,0,0,0,1,0,1,0,0,0,0,0,0,0,0,0,0;
        0,0,0,0,0,0,2,0,0,0,0,1,0,0,0,0,0,0,0,0;
        0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
        0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0];

 %defining n as n100 or n25. This can be changed
 N = n100;
 L = length(N);

```

```
%W(i) is the set of charging locations that can partially cover polygon i
W = zeros(1,L);

%i is the set up poligons dividing Turin (either 100 or 400)
i = [1:L^2]; % i = j
```

B.2 Partial Coverage Script

```
% ---------------------------------------------------------------------
%Determining M - the set of poligons FULLY covered by a charging station
% ---------------------------------------------------------------------

%Determining full coverage of all central points
for x = 2:L-1
    for y = 2:L-1
        if N(x,y) ~= 0 %check to see if the poligon contains a charging station
            M(x,y) = 1;
        elseif (N(x-1,y)+N(x+1,y)+N(x,y-1)+N(x,y+1)+N(x-1,y-1)+N(x-1,y+1)+N(x+1,y-1)+N(x+1,y+1)) >= theta
        % above elseif checks if adjacent poligons contain enough charging
        % stations to satisfy full coverage
            M(x,y) = 1;
        end
    end
end

%Determining full coverage for the 4 corner points
%corner point 1,1
if N(1,1) ~= 0
    M(1,1) = 1;
elseif (N(1,2)+N(2,1)+N(2,2)) >= theta
    M(1,1) = 1;
end
%corner point 1,L
if N(1,L) ~= 0
```

```
    M(1,L) = 1;
elseif (N(1,L-1)+N(2,L)+N(2,L-1)) >= theta
    M(1,L) = 1;
end
%corner point L,1
if N(L,1) ~= 0
    M(L,1) = 1;
elseif (N(L,2)+N(L-1,1)+N(L-1,2)) >= theta
    M(L,1) = 1;
end
%corner point L,L
if N(L,L) ~= 0
    M(L,L) = 1;
elseif (N(L-1,L)+N(L,L-1)+N(L-1,L-1)) >= theta
    M(L,L) = 1;
end



%Determining full coverage for the first and last column/rows
%rows 1 and L
for x = 2:L-1
    %row 1
    if N(x,1) ~= 0
        M(x,1) = 1;
    elseif (N(x-1,1)+N(x-1,2)+N(x,2)+N(x+1,2)+N(x+1,1)) >=
       theta
       M(x,1) = 1;
    end

    %row L
    if N(x,L) ~= 0
        M(x,L) = 1;
    elseif (N(x-1,L)+N(x-1,L-1)+N(x,L-1)+N(x+1,L-1)+N(x+1,L))
       >= theta
        M(x,L) = 1;
    end
end

%columns 1 and L
for y = 2:L-1
  %colunn 1
  if N(1,y) ~= 0
```

```
        M(1,y) = 1;
    elseif (N(1,y-1)+N(2,y-1)+N(2,y)+N(2,y+1)+N(1,y+1)) >= theta
        M(1,y) = 1;
    end

    %colunn L
    if N(L,y) ~= 0
        M(L,y) = 1;
    elseif (N(L,y-1)+N(L-1,y-1)+N(L-1,y)+N(L-1,y+1)+N(L-1,y+1)) >= theta
        M(L,y) = 1;
    end
end

% -----------------------------------------------------------------------
%Determining W - the set of poligons PARTIALLY covered by a charging station
% -----------------------------------------------------------------------

%Determining partial coverage of all central points
for x = 2:L-1
    for y = 2:L-1
        if N(x,y) ~= 0 %check to see if the poligon contains a charging station
            W(x,y) = 0;
        elseif (N(x-1,y)+N(x+1,y)+N(x,y-1)+N(x,y+1)+N(x-1,y-1)+N(x-1,y+1)+N(x+1,y-1)+N(x+1,y+1)) >= omega
        % above elseif checks if adjacent poligons contain enough charging
        % stations to satisfy partial coverage
            W(x,y) = 1;
        end
    end
end

%Determining partial coverage for the 4 corner points
%corner point 1,1
if N(1,1) ~= 0
    W(1,1) = 0;
```

```
elseif (N(1,2)+N(2,1)+N(2,2)) >= omega
    W(1,1) = 1;
end
%corner point 1,L
if N(1,L) ~= 0
    W(1,L) = 0;
elseif (N(1,L-1)+N(2,L)+N(2,L-1)) >= omega
    W(1,L) = 1;
end
%corner point L,1
if N(L,1) ~= 0
    W(L,1) = 0;
elseif (N(L,2)+N(L-1,1)+N(L-1,2)) >= omega
    W(L,1) = 1;
end
%corner point L,L
if N(L,L) ~= 0
    W(L,L) = 0;
elseif (N(L-1,L)+N(L,L-1)+N(L-1,L-1)) >= omega
    W(L,L) = 1;
end

%Determining partial coverage for the first and last column/
    rows
%rows 1 and L
for x = 2:L-1
    %row 1
    if N(x,1) ~= 0
        W(x,1) = 0;
    elseif (N(x-1,1)+N(x-1,2)+N(x,2)+N(x+1,2)+N(x+1,1)) >=
        omega
        W(x,1) = 1;
    end

    %row L
    if N(x,L) ~= 0
        W(x,L) = 0;
    elseif (N(x-1,L)+N(x-1,L-1)+N(x,L-1)+N(x+1,L-1)+N(x+1,L))
        >= omega
        W(x,L) = 1;
    end
end

```

```
%columns 1 and L
for y = 2:L-1
  %colunn 1
  if N(1,y) ~= 0
      W(1,y) = 0;
  elseif (N(1,y-1)+N(2,y-1)+N(2,y)+N(2,y+1)+N(1,y+1)) >= omega
      W(1,y) = 1;
  end

   %colunn L
  if N(L,y) ~= 0
      W(L,y) = 0;
  elseif (N(L,y-1)+N(L-1,y-1)+N(L-1,y)+N(L-1,y+1)+N(L-1,y+1))
     >= omega
      W(L,y) = 1;
  end
end
```

B.3 Linear Program Script

```
%Linear programming solver to determine the optimal number of
   EV chargin
%stations

run setup.m %setup and defining variables
run partial_coverage.m %determines full and partially covered
   poligons

%Setup for decision variables
%-------------------------------------------
%xj binary decision variable if a charging station is located
   in location j
%yi binary decision variable if poligon i is covered by at
   least one charging station
%vi binary decision variable if poligon i is partially covered
   by at least one charging station
li = length(i);
li2 = 2*li;
li3 = 3*li;
li4 = 4*li;
ymin = reshape(M,[li,1]);
vmin = reshape(W,[li,1]);
binN = 0.9*(N>0);
```

```
xmin = reshape(binN,[li,1]);
x = xmin';
y = zeros(1,li);
v = zeros(1,li);

%Objective function f
%------------------------------------------------
%minimise sum of c*x(j)
 f1 = zeros(1,li); %yi and vi parts of f
 f2 = c*ones(1,li); %xj part of f
 f = [f1 f1 f2]; %f = [y;v;x]


%Subject to
%------------------------------------------------
%A are the coefficients of the <= constraints
%b are the right hand side constraints of the coefficients of A

 Ai = eye(li); %identity matrix
 A0 = zeros(li);
 nearA = ones(li)-tril(ones(li),-2)-triu(ones(li),2)-Ai; %horizontally adjacent points
 nearA = nearA+tril(ones(li),-L)-tril(ones(li),-(L+1))+triu(ones(li),L)-triu(ones(li),(L+1)); %vertically adjacent points
 w = reshape(W,[li,1]);

 A4 = [-w' beta*-w' zeros(1,li)];

%Defining A - left hand side conditions
 A = [Ai A0 -Ai; A0 (theta*Ai) -nearA; Ai Ai A0; A4];

%Defining B - right hand side conditions
 b1 = zeros(1,li); %xj part of f
 b3 = ones(1,li); %yi and vi parts of f
 b = [b1 b1 b3 -alpha*sum(w)]; %f = [x;y,v] old -- b = [b1 b1 b3 -alpha*sum(w)];
 b = reshape(b, [(li3+1),1]);
 b = reshape(b, [1,li3+1]);


%Defining the upper and lower bound conditions for variables
 lb = zeros(1,li3);
 lb((2*li)+1:3*li) = xmin;
```

```
ub = ones(1,li3);

%Aeq are coefficients of equality constraints
%bea are right hand side of the quality constraints
Aeq = [];
beq = [];

%output X is the state of the decision variables
%output z is objective function
intcon = 1:li3;

%defines the options as an integer problem since the decision
    variables are
%binary, and sets macimum run time and display parameters
options = optimoptions('intlinprog','MaxTime',60,'Heuristics','
    basic','Display','final');
[X,Z] = intlinprog(f,intcon,A,b,Aeq,beq,lb,ub,options);


map = reshape(X((li2)+1:end), [L,L]); %binary map of all
    charging locations
delta = map - (N>0); %binary map of new charging locations
networkcost = c * sum(sum(delta));
```