QATAR UNIVERSITY

COLLEGE OF ENGINEERING

AN OPTIMIZATION FRAMEWORK FOR ELECTRIC VEHICLES CHARGING STATIONS ALLOCATION USING DEMAND BASED ON CITY TRAFFIC COUNT

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ABSTRACT

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Selecting good locations for the placement of Electric Vehicle (EV) public charging stations is important for the uptake of EVs. As EVs are considered to have lower green gas emissions to internal combustion engines, the uptake of EVs is considered better for the environment. Many factors are involved in the location-allocation problem for EV public charging stations, such as understanding demand, needs assessment, identifying possible locations, and selecting a facility location optimization model. This study provides a framework to improve demand identification and estimation accuracy and reliability by using traffic data and VISUM traffic simulation software. The case study of Doha is presented by applying three facility location optimization models. The set covering model results provide well-distributed stations, while the maximum coverage model locates stations in a concentrated area.

DEDICATION

This work is dedicated to my family, whom I can’t be who I am without them.

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CHAPTER 1: Introduction

Climate change and the continuous rise have been among the most researched and discussed topics in the last decade. Governments have taken many measures and legislation to control their greenhouse gas emissions. Gasoline cars have been recently the second highest source of greenhouse gases after factories and plans. Electric vehicles (EVs) are considered an alternative to internal combustion engine vehicles as they cause lower pollution and are energy-efficient when electricity is generated by natural gas or renewables (Al-Buenain et al., 2021).

EVs started spreading actively around 2010 in several countries. However, the market penetration of EVs varies in different countries due to many factors such as government policies, incentives, and other socio-economic factors.

Countries are adopting strategies to promote EVs, especially China, the USA, and Europe. As a result, global EV sales in 2017 surpassed 3 million cars and are expected to grow, Norway has the highest share of EVs on the road, and more than 400,000 charging stations were present globally in 2017 (Nicholas & Hall, 2018). Still, these markets are not yet mature and require further development of policies, battery and charging technologies, and charging infrastructure.

However, other EV markets, especially the Middle East (Qatar), are in early-stage requiring planning of public charging. Due to its small population and big industrial activities, Qatar is considered one of the highest polluting countries (when measured per capita). Qatar’s government is aware of the dangers of pollution, and it has started many new initiatives related to the environment. In November 2022, Qatar will host The FIFA World Cup 2022, and to show its environmental awareness, Qatar has made a promise to have the first carbon-neutral world cup.

With the rapid growth of the country and the important events that it is participating in, Qatar’s population is growing very rapidly. This rapid population growth is a major concern for the government of Qatar, which wishes to control the number of cars on its roads and reduce the emissions in its urban cities. All these things have led to Qatar announcing it is National Development Vision 2030, which is focused mainly on the three pillars of sustainability (Environmental, Human, and Economic Development).

The promotion of EVs in Qatar is a strategy believed to help achieve the targeted emissions reductions where Qatar targets to have at least 10% of its vehicles on roads as Electric Vehicles by 2030.

The limited range of EVs, usually 250 km – 400 km, is considered a major barrier in the wide adoption of EVs, and the deployment of more public charging infrastructure is a possible way to reduce this barrier.

Multiple factors and stakeholders are involved in planning charging facilities, and the need for public charging stations differs between countries. However, studies suggest that possible EV charging stations should be destinations like shopping malls, parks, hospitals, and university parking (Helmus et al., 2018).

The ownership of home charging is a major factor affecting the modeling and location of charging stations. In countries (regions) with a low ownership rate of home charging, deployment of public chargers is important to promote use as this will be a necessity and the main charging mode. Whereas in countries with a high ownership rate of home charging, providing public chargers gives convenience and assurance to the user as they will be the second option after home charging. In Beijing, 30% of EV drivers rely entirely on public charging networks as they do not have home chargers (Pan et al., 2020). In countries like Norway, Germany, and the US, reliance on public charging is lower as home charging is available to most users. Public chargers need to be well planned and located to capture the demand and be effectively utilized.

Facility location problem models have been used in many domains such as emergency response, fire, medical, school, waste management, and hospitals; the objective of different models varies based on the purpose. For example, in applying the facility location model for EV public charging stations, the convenience of access to the location is a major factor. At a public level, slow chargers require 30min to two hours to charge the EV; thus, customers are less likely to wait this time in a place that is not convenient.

1.1 Research problem

Improper placement of EV charging stations could result in inefficient resource utilization, failing to meet the business objectives or profitability. Similarly, it would lower the uptake of EVs in the country, as visibility of public charging stations is highly associated with EV uptake. The EV public charging stations location-allocation problem consists of several aspects, most importantly1) understanding the demand points, 2) estimating the demand at the points, 3) understanding needs for public charging, 4) identifying possible locations, and 5) selecting the facility location optimization model. In addition, the scope and the size of the area of analysis influence the problem definition. For example, approaching the problem of public charging stations within a business neighborhood would be different from the approach used to place public charging stations in a city. The proposed framework is shown in the figure below.

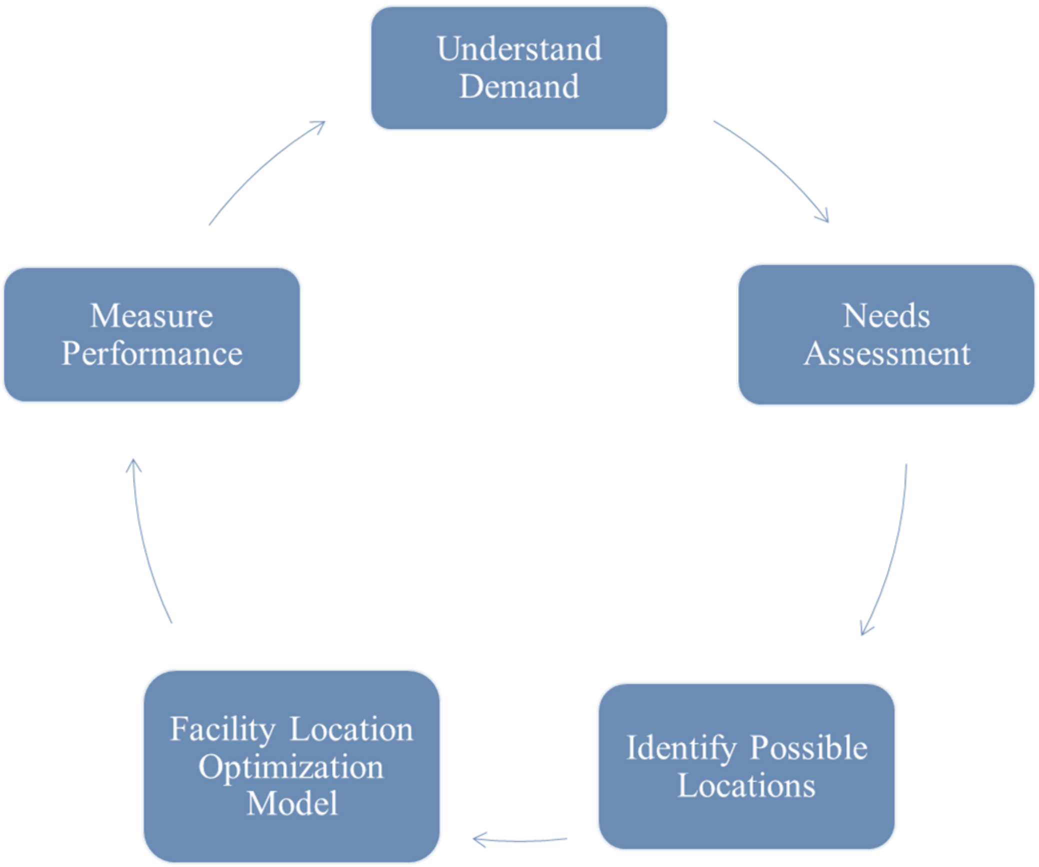

Figure 1: Proposed framework

1.2 Research Questions

To achieve efficient utilization of the public EV charging stations, the accuracy and reliability of demand are required. Therefore, the research questions for this study are:

1. What factors affect electric vehicles demand?
2. How to estimate the charging demand of an early electric vehicle market?
3. How many public charging stations are required for an early EV market?
4. What criteria influence the selection of possible locations for public charging stations?
5. Where should the EV public stations be located?

1.3 Objectives

This research has three objectives.

1- To study the demand assessment models and determine the suitable method, representing demand.

2- To identify possible locations for EV charging stations in early EV markets..

3- To optimize the location of public charging stations using two classic location models.

1.4 Research Methodology

The methodology used to answer the research questions and achieve the objectives is briefly described in this section. First, the literature review will identify the gaps and understand the previous models. Then in Stage one, equations and models will be used to forecast the total charging demand. In Stage two, origin/destination data obtained from sensors placed on roads will be used to understand and forecast the demand nodes. In Stage Three, the objectives for the public charging stations and the possible locations will be identified. Finally, in Stage Four, the facility location optimization models will be used to optimize the locations of the public charging stations.

1.5 Research Contribution

This research provides a framework for approaching the location-allocation of EV public charging stations, improving the accuracy and reliability of the demand and number of required stations. This is significant because it provides city planners with insights to optimize the number and placement of stations, increase stations utilization, and reduce waste.

1.6 Report Outline

This study is organized as follows. Chapter 1 introduces the topic and presents the research problem, objectives, and research framework. In chapter 2, background on EVs is provided and a summary of the related work. In chapter 3, the research methodology was used to answer the research questions. Chapter 4 then present the study area and the data collection. In chapter 5, the results are presented. Finally, chapter 6 concludes the study and provides recommendations and future work.

CHAPTER 2: Literature Review

This chapter aims to give background about EVs and the charging modes. In addition, it provides a review of the studies associated with EVs to understand the factors affecting the uptake and the need for charging. Finally, it summarizes the literature on EV charging stations allocation studies to understand the possible locations, demand estimation, and location-allocation models.

2.1 EVs and charging levels

This section explains different available electric vehicles and charging modes to develop a common understanding.

Electric vehicles are under three categories, hybrid (HEV), plug-in hybrid (PHEV), and Plug-in electric vehicle (PEV), which is sometimes referred to as battery electric vehicle (BEV). The hybrid electric vehicle has a battery installed in addition to the internal combustion engine. The battery recharges can only recharge while the vehicle is in motion using a generator, and the generated energy is used to drive the vehicle. The benefit of an HEV is that it increases the range of the vehicle and improves its efficiency. The PHEV has a battery that can be charged at stations or homes and the fuel tank. This option provides flexibility to drivers. However, the disadvantage is the high cost and the little storage space as the battery and the electric motor take space. The BEV relies on the battery as the only energy source. The BEVs are most users utilizing the public chargers in current EV markets. Therefore, in the remainder of this paper, the reference to BEV will be EV. The EV market is expected to be dominated by BEVs and HEV, and PHEVs could become obsolete (Rietmann & Lieven, 2019).

The time to charge the EV is much more than the time required to refuel at a petrol station. Depending on the charging mode and equipment, charging can take 30 minutes or more than 8 hours. This is one of the reasons why EV charging requirements need to be evaluated differently than petrol stations. Different chargers are available to charge the EV. Four charging modes are defined by the International Electrotechnical Commission (IEC). The main difference between the modes is the possibility to control charging power and the level of safety. The four modes are mode 1, mode 2, mode 3, and mode 4. Modes 1-3 use AC power and are slow level 1 and level 2 chargers used at home, work, and public locations. Mode 4 is the DC fast charger delivering 50 kW up to 350 kW (Nicholas & Hall, 2018). The table below summarizes the available charging types.

Table 1: EV Charging types

Type	Mode	Level	Use
Standard AC Slow (~ 1.4 kW)	1	1	Home
AC Slow (up to 11 kW)	2	2	Home / Work
AC Slow (11 kW – 22 kW)	3	2	Work / Public
DC Fast (up to 150 kW) / DC Super fast (More than 150 kW)	4	3	Public / Highways

2.2 Factors affecting EV uptake

Some factors affect the uptake of electric vehicles in different regions; these can be grouped under buyer characteristics, enabling environment, and external factors. This section will discuss these to identify who is more likely to be an early adopter of EVs, an enabling context in terms of policies, infrastructure, population density, energy prices, and some known other influencing factors.

Studies have been conducted to understand the characteristics of buyers of electric vehicles. For example, Axsen et al. (Axsen et al., 2016) conducted an in-depth survey in Canada and found that responders with multi-vehicle households are more likely to be adopters of EV. Similarly, respondents owning an EV have higher income and education levels, live in a single-family standalone house, and access home charging. Moreover, early adopters of EV were likely to be middle-aged men. To investigate whether single or multi-vehicle households were more likely to adopt an EV, Jakobsson et al. (Jakobsson et al., 2016) analyzed GPS travel data of single and multi-vehicle households in Germany and Sweden to understand their driving patterns. They conclude that the second car drives fewer long distances and is more suited to replace an affordable EV with a small battery.

Other researchers report similar findings in other countries. Morton et al. (Morton et al., 2018) analyzed the population characteristics in different regions in the UK with high sales of EVs. They report that regions with higher personal income, higher education level, and higher employment status are ahead in EV adoption than others. Bruckmann et al. (Brückmann et al., 2021) used the revealed preference approach to analyze the individual and spatial characteristics of actual buyers of EVs in Switzerland. There study provided insights on adopters in regions without strong EV policies. As Switzerland does not offer strong policies like others such as Germany or UK were, for example, 4000 € purchase premia are offered. Their study reports similar findings as the adopters of EV have higher income and education levels, are more likely to be multi-car households, and are owners of standalone houses.

The enabling environment is an important factor as well. It is policies such as regulations and incentives, the availability of charging infrastructure, and the range, reliability, and cost (Higueras-Castillo et al., 2021). Studies report the effectiveness of policies that increase the market share of EVs, which, when canceled, resulting in a drop in sales (Wang et al., 2019). Yao et al. (Yao et al., 2020) developed econometric models to study the effect of different policies such as subsidies, waiver on fees, and others on EV sales in 13 countries. The results showed that subsidies, waivers, and mandates positively affected EV sales volume. The presence of public chargers proved very effective as an increase of 1% in the density of slow public chargers caused a 0.7% increase in EV uptake.

Other external factors also affect EV uptake in different regions. For example, the businesses benefiting from the conventional private cars market have low interest in EV uptake and will push to delay it (Rietmann & Lieven, 2019).

When the abovementioned factors are combined, they result in greater EV uptake, as reported in Rietmann & Lieven (Rietmann & Lieven, 2019). Their model showed that regulations, financial incentives, and availability of charging infrastructure positively influence EV uptake. They studied the interaction between these and reported that the interaction between the financial incentives and the maturity of the charging infrastructure has a very strong positive impact on EV uptake. This was also observed in Yao et al. (Yao et al., 2020), where US and Korea had similar policy incentives score in their model to Norway; however, EV uptake in Norway was higher.

2.3 Needs for charging infrastructure

Having access to home charging is a critical factor in EV uptake, and recent research shows that 50-80% of charging occurs at home (Hardman et al., 2018). This section will discuss the needs for charging and how they differ between countries. Several researchers approached this by investigating the daily driving range compared to the BEV range. (Pearre et al., 2011) studied the case where EVs are assumed to charge every night at home and start the next day with a full charge. By monitoring 470 vehicles for more than 50 days in Georgia, they found that a large population of drivers can meet their driving needs with affordable BEVs. The study points out that more drivers can meet their needs by charging during the day on some days; they call it "Day requiting adaption." (Jakobsson et al., 2016) detailed the study further in Germany and Sweden and analyzed the annual vehicle kilometers traveled (VKT) for single and multi-car households to understand the days requiring adaption. They report that drivers with annual VKT above 40,000 need to use public charging at least once a week.

(Funke et al., 2019) conducted an international comparison to investigate the need for charging infrastructure. These needs differ depending on several factors. Most important is the availability of private home parking. Other factors are the Gini indices, car dependency, GDP per capita, the share of the urban population, population density, and the average daily driving distances. In Netherland, as the number of detached houses is low, many public slow charging stations are built to substitute for home charging. In countries with a high share of detached houses, less public slow charging is required. Moreover, fast-charging stations are needed on highways for long-distance trips or in highly populated areas with no access to private parking.

Analyzing real-world data of charging stations and number of BEVs per million population. (Nicholas & Hall, 2018) report a different number of BEVs per charging station in different countries. As countries have different framework conditions, as discussed above. Researchers such as (Chakraborty et al., 2019) report that the price of electricity in different locations (home, work, public) has a significant effect on the choice selection for the charging place. Finally, studies point out that further research is required to understand how much charging is needed.

2.4 Possible locations for EV charging stations

Identifying possible locations to locate EV charging stations is important for the effective utilization of the station. This can be achieved by understanding EV users' preferences and criteria for possible locations. For example, motorway service stations, existing gas stations, and shopping facilities are possible locations for fast charging stations (Philipsen et al., 2016). In Japan, parking service providers and gas stations are possible locations for fast charging stations. Similarly, In Norway, Tesla superchargers are placed in shopping centers, cafes, and roadside restaurants. Many locations are used for fast and slow charging stations in the UK, such as train stations, airports, shopping malls, and supermarkets (Deb et al., 2018). This indicates that charging stations are placed in points of interest (POI).

Two strategies for locating EV charging stations were used in Netherland. The first strategy, "demand-driven," placed charging stations based on users' requests near their homes. The second strategy placed stations near public facilities such as shopping malls and government buildings. When analyzing the "demand-driven" charging stations, they were not uniformly distributed in the city and concentrated in high-density areas, mainly because EV users do not have access to private home charging. As a result, strategically placed charging stations were used by more unique users but had lower utilization. The study concluded that both strategies complement the other as they performed well on different objectives (Helmus et al., 2018).

2.5 EV demand estimation

Effective allocation of EV charging stations relies on the method used to estimate demand and to understand where the actual charging demand is. The node-based approach assumes the demand is concentrated at a certain point. The population distribution is used as a proxy to identify the demand in some studies (Brown et al., 2021; Sun et al., 2020). (S. Y. He et al., 2016) identified the charging demand of a community by considering several demographic data such as family size, income, and age. (Sadeghi-Barzani et al., 2014) used a similar approach to estimate demand by using the vehicle ownership data of each region. These demand points may not be accurate as knowing where EVs are concentrated may not necessarily be where they need to charge. Especially in the case where EV users have access to home charging. (Frade et al., 2011) used two approaches to estimate the demand; for the nighttime demand, the population data was used, assuming EV users have no access to home charging; for the daytime demand, the type of buildings and the volume of employment of a region indicated the demand. (Liu, 2012) used the distribution of gas stations as a proxy to estimate the charging demand of a region.

Another demand estimation approach is path-based, which uses the traffic volume data, which requires more data than the static node-based approach. To estimate the demand for fast charging stations on highways, (Jochem et al., 2019) used traffic volume data. Other researchers used the tour-based approach, which uses much more data. This approach uses individual users' travel data. (Dong et al., 2014) used the GPS tracking data of users in a study to model the EV charging demand. (Pan et al., 2020) used drivers trip destination data of 5183 participants in a travel survey.

2.6 EV charging stations location-allocation models

Depending on the model representing the demand, several location models could be used to optimize the allocation of EV charging stations. The path-based traffic volume (flow) can be used in the flow capturing location model (FCLM) to capture most flow. This model was first introduced by (Hodgson 1990).

Multiple location models are available when considering the demand as concentrated in a point. The P-median location model (Hakimi, 1965) minimizes the sum of distances traveled from different demand points. (Hakimi, 1965) also introduced the p-center model, which targets to place the facility to minimize the longest distance to the demand point. The set covering model aims to place the minimum number of facilities to capture all demand points within a certain radius. This model is usually used in emergency service stations allocation. A drawback for the set covering is that it does not consider the amount of demand and gives equal weight to all demand points. The Maximum coverage model introduced by (CHURCH & VELLE, 2005) solves this issue by accounting for the demand size at each point and targeting to capture most demand with a specified budget within the critical coverage distance.

Studies used these models with different objective functions. The main optimization goals were to minimize the distance to a charging station; minimize the infrastructure cost for a given demand, and maximize the number of EVs charged.

2.7 Chapter summary: gap analysis

Among the EVs, BEVs require the EV charging infrastructure. HEVs and PHEV could be a transition, and BEVs the destination. Public EV charging infrastructure could be slow, at public facilities or work, or Fast charging stations at highways or in highly populated areas as an alternative to home charging. The uptake of EVs depends on multiple factors such as buyer characteristics, the enabling environment, and external factors. Moreover, the needs for public EV charging stations are different between countries and between regions. Therefore, the development of charging infrastructure should be investigated considering wider aspects. The demand estimation method is critical in solving the EV station's location problem. The demand node-based traffic volume or Points of Interest (POI) are alternative methods. Table 2 (below) provides a summary of selected papers.

Table 2: Literature review summary

Paper	**Demand estimation**	**Possible locations**	**Optimization model**	**Scope & city**
(S. Y. He et al., 2016)	EV adoption potential index of a community (313 demand points)	Public car parks & Petrol stations 1029 possible location	SCP, MCLP & P median	Beijing city
(Pan et al., 2020)	Household travel survey	395 Traffic analysis zones 0.2^2 km-1.7^2km	Tour based Simulation	Beijing 302^2km
(Liu, 2012)	Using the number of petrol stations in the area as a proxy to estimate demand	N/A	MCLP	Beijing
(Frade et al., 2011)	Census data	290 car parks	MCLP	Lisbon $8km^2$ neighborhood
(Sun et al., 2020)	Node-based & Traffic volume	N/A	MCLP FCLM	China

Paper	Demand estimation	Possible locations	Optimization model	Scope & city
(Dong et al., 2014)	Tour-based	Top 500 destinations	Tour-based	Seattle, USA
(Namdeo et al., 2014)	Socio-economic traits “hotspots” Travel pattern	N/A	weighted-overlay statistics	Predict spatial distribution of charging needs
(Wagner et al., 2013)	N/A	Box area 100m x 100m	MCLD	“Attractiveness of a charge point by its surrounding POI’s
(J. He et al., 2018)	Tour based	N/A	FCLM	N/A

CHAPTER 3: Research Methodology

This chapter explains the research methodology used to answer the research questions and achieve the objectives. Figure 2 below shows the graphic representation of the research methodology. The methodology has seven stages, initiations, stages one through five, and ends with closure. In the initiation stage, an initiative literature review is conducted to identify gaps in the literature, identify the research problems, and develop research questions and objectives. Stage one then aims to improve the accuracy of forecasting the total charging demand by forecasting the market share of EVs (step 1), forecasting the number of EVs on the road (step 2), and finally forecasting the charging demand (step 3).

Stage two aims to improve the demand estimation at nodes and the reliability of the demand points (steps 4-5). Stage three then aims to identify convenient locations for the specific type of charging infrastructure (steps 6 and 7). Once the demand nodes and possible locations are identified, stage four aims to optimize the locations of charging stations by determining the required number of stations (step 8) and applying the location optimization model to locate charging stations (step 9). Stage five will then validate the framework (step 10) by applying the model to the existing charging stations to observe how much demand is satisfied. The final stage is the closure, where the results, conclusions, recommendations, limitations, and future work will be reported.

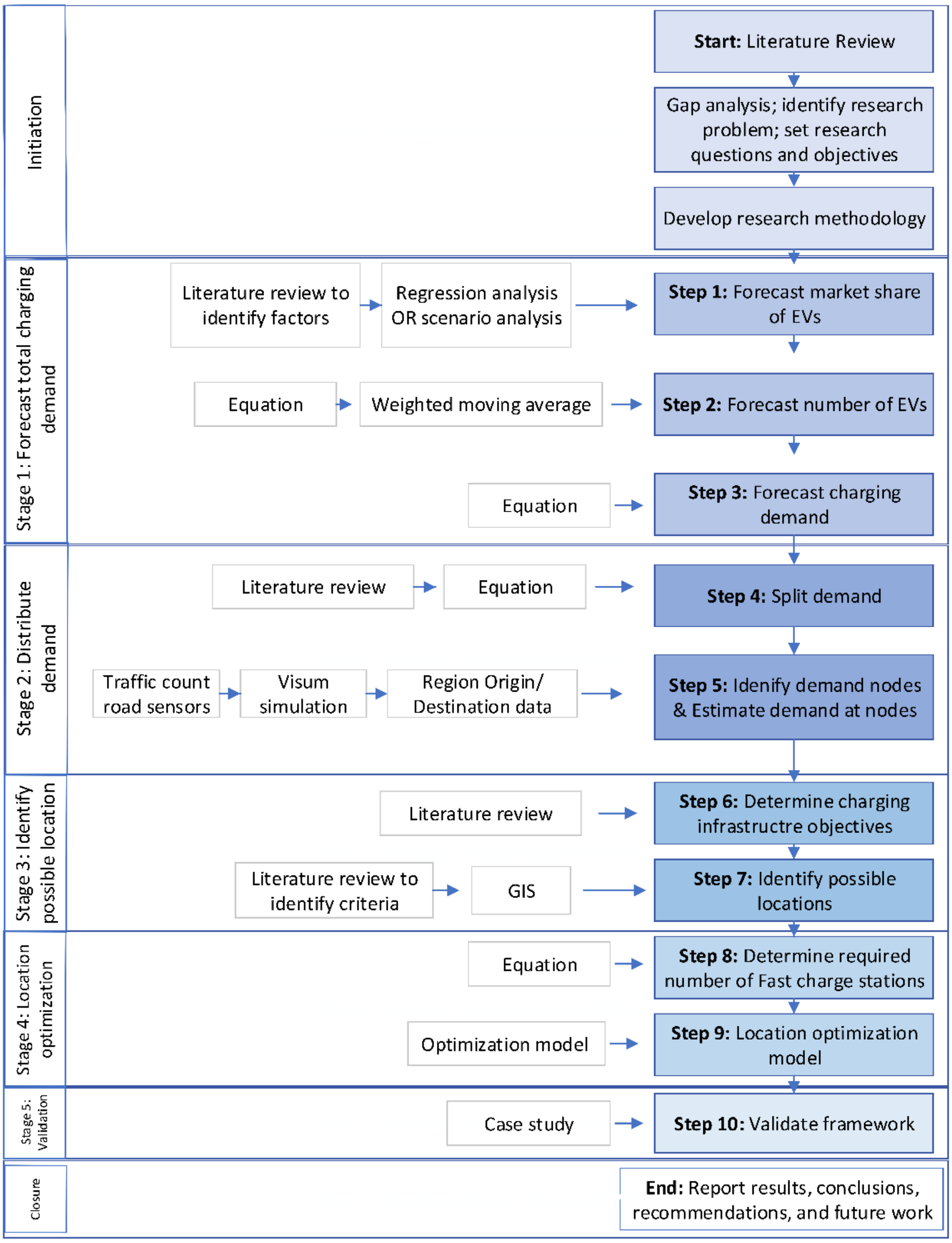

Figure 2: Research Methodology

The ten steps of the research methodology are explained and discussed in the sections below.

- **Step 1: Forecast market share of EVs**

This step aims to forecast the market share of EVs in the region of analysis.

To estimate the market share of electric vehicles, a relationship is established with the influencing factors. These factors are discussed below.

Table 3: Factors influencing EV market share

Factors affecting EV Market Share	**Value**
EV specification	Range, battery size, cost
Buyer characteristics	GDP per Capita
Regulations / Incentives / Govt. target	Binary
Charging infrastructure	Public chargers' density
Local travel profile	Average traveled daily distance by car (VKT)
EVs on road	Number of EVs on road
Gasoline to electricity price ration	Price ratio

The first factor is related to the developments in EV technologies and the current EV specification, mainly the range, battery size, and cost. The second factor is related to the buyer characteristics; income, education, employment, and family size, and these are the sub-factors. However, this factor can be represented by the GDP per capita if data for the sub-factors are not available. The third factor is the presence of supporting regulations (e.g., standards for home charging), incentives (e.g., subsidies and waivers), and government commitment (e.g., vision and targeted number of EV). Forth is the presence and maturity of charging infrastructure, as visualizing chargers on the streets encourages potential EV buyers to adapt an EV. The fifth factor is the local travel profile, which is how many kilometers does the population travel by car. Another factor is the number of EVs on the road, affecting users' perception and willingness to buy an EV. Finally, the gasoline to electricity price ratio plays an important role in predicting the market share of EVs, as it affects the economic decision by the buyer. Therefore, as many factors are involved in the process, a regression analysis, linear or non-linear, could be developed to predict the market share.

As this is not possible due to limited time and resources in this research, a scenario for the market share of EVs in the next three years will be developed. This scenario considers previous years' EV market share for the city of analysis, the EV market share of different countries, and the international energy agency (IEA) outlook.

- **Step 2: Forecast number of EVs**

The following Equation can represent the forecasted number of EVs:

$$EV_t = EV_{t-1} + PVS_{t-1} \times m_{EV} \qquad \text{Equation (1)}$$

Where

$t = year\ of\ analysis$

$m_{EV} = Market\ share\ of\ EVs$

$EV_t = Number\ of\ EVs\ in\ year\ t$

$EV_{t-1} = Number\ of\ EVs\ in\ year\ t-1$ (Average 3 years)

$PVS_{t-1} = Private\ vehicles\ sales\ in\ year\ t-1$

- **Step 3: Forecast charging demand**

To forecast the charging demand of a city, two factors are the most influence are the local travel profile and the EV energy consumption. The local travel profile is the average daily traveled distance by private cars, and the EV energy consumption is the required kWh to travel 100 km. Therefore, the following relationship is established.

$$Daily\ charging\ demand: C\ (kWh) =$$
$$f(EV\ energy\ consumption, local\ travel\ profile\ (VKT)) \qquad \text{Equation (2)}$$

The average EV battery capacity in 2020 was 55 kWh, with an average range of 350 km up from 200 km in 2015 (International Energy Agency, 2021). In addition, the EVs' energy consumption ranged between 10.4 to 29.5 kWh / 100 km, with an average energy consumption of 20.2 kWh / 100 km (EV Database, 2021).

For the local travel profile, 40000 km per annum is considered high, which results in 109 km per day. Therefore, to be conservative when forecasting the daily charging demand, the average daily traveled distance of 150 km and the average energy consumption of 20.2 kWh / 100 km will be used. This results in a daily demand of 30.3 kWh per EV.

- **Step 4: Split demand**

In contrast to petrol refueling, EV users have the flexibility to charge in different settings and modes, which generates different demand nodes. These are overnight home charging, day charging at points of interest (POIs) such as work and other destinations, and stations at highways between cities.

With the current EV and charging technologies, EV home charging is the primary charging source, where 50-80% of charging occurs there (Funke et al., 2019). Therefore, in communities with standalone detached houses with private garages and in areas that offer private parking for each apartment, the requirement for deployment of public charging infrastructure is not relevant. However, in areas with a low rate of private parking, the deployment of public charging stations is required. These demand points will be referred to as community demand points.

Therefore, the demand is divided by the three modes in the following relation:

$$Demand\ for\ home\ charging: C_h = a \times C \qquad \text{Equation (3)}$$

$$Demand\ for\ POI\ charging: C_{poi} = b \times C \qquad \text{Equation (4)}$$

$$Demand\ for\ highway\ charging: C_h = c \times C \qquad \text{Equation (5)}$$

$$a + b + c = 1 \qquad \text{Equation (6)}$$

Where

$a = share\ of\ home\ charging$

$b = share\ of\ POI\ (destination)\ charging$

$c = share\ of\ highway\ charging$

This research will only focus on demand from Equation (4).

- **Step 5: Demand nodes identification and demand estimation at nodes**

Several methods exist in identifying demand nodes and estimating demand at nodes. However, few papers in the literature consider the difference between the demand points. To explain this point further, the following example is provided. When planning the locations for public charging stations at points of interest, some researchers use the population data of communities as the demand nodes and measure the distance between the community and the possible locations (points of interest). This approach's accuracy and reliability are not high, as the users' destinations and where they need to charge are different from their house. Table 4 provides some of the methods used to identify and measure different demand points.

Table 4: Demand identification and estimation methods

Demand	Method
Community demand for home charging	Population density, community census data, building codes
POI (destination)	Origin / Destination traffic data (GPS tracking data, pneumatic tube sensors on the road, ultrasound sensors on the road, household travel survey)
Highway	Traffic flow data

When planning public stations for community charging in communities with a low ownership rate of home charging, the population density, population census data, and building codes could be used as accurate and reliable methods for identifying and estimating demand.

For the placement of public charging stations at points of interest (POIs), the origin/destination data could be reliably used. These data could be obtained by GPS tracking devices placed in users' cars, road traffic count sensors, or household travel surveys (Chen et al., 2013; Pan et al., 2020).

The Origin/ Destination data (O/D) will be obtained from PTV Visum traffic simulation software to identify the POI demand points in this research. This software utilizes traffic flow data captured by pneumatic tube sensors and ultrasound sensors placed on roads to model the traffic in the city. A matrix with O/D data between regions is extracted and used to estimate the demand at different nodes.

- **Step 6: Determine charging infrastructure objectives**

As home charging is the primary charging mode with the current technology, the *first* *objective* is to ensure each EV user has access to home charging or an alternative. Alternatives to home charging could be either level 2 public chargers in public parking spaces or fast-charging stations placed in petrol stations in communities without public parking spaces. Meanwhile, regulations and standards for home charging must be available and regularly updated for users with access to home charging.

The *second objective* would be to place L2 chargers in points of interest (POIs). These POIs are the destinations where people can park in the afternoons and evenings for more than 30 minutes. Depending on the local travel profile, on most days, most EV users will not require these and may need to use them once a week when they need to drive longer than the EV range. As a result, the required capacity in these stations is difficult to predict initially. Therefore, this framework recommends that these stations have the flexible capacity and have provisions to increase or decrease charging ports depending on the observed utilization. The objective is to place stations to capture the most demand.

Once home charging or an alternative to it is provided to EV users, and POI has L2 chargers, the *third objective* would be to provide a minimum number of fast-charging stations to cover the entire city within a driving distance of fewer than 15 minutes. This is taken as a 2 km distance in the urban area considering the traffic. These are placed to assure EV users that they are always near an EV fast-charging station (FCS). The possible locations for these could be existing petrol stations or metro stations parking. Similarly, as the capacity is difficult to predict initially, these would need to have provision to add or remove charging ports depending on the utilization. Solar panels can supply electricity to the fast charging ports to reduce dependency on the electricity grid and improve their sustainability. As the number of EVs increases, more stations could be added to reduce the time from 15 minutes to 10 minutes.

The *final objective* is to provide at least one fast-charging station on highways between cities. The number of stations will depend on the highway traffic volume and the share of EVs. Initially, one fast charging port supplied by solar panels can be placed in the middle of each highway between cities. Then, depending on the utilization, and as the share of EVs increases, more ports and stations will be added.

The case study in this research will be on the third objective, assuming users will have access to home chargers, and public places will provide level 2 (L2). The POI demand, C_{poi}, could be satisfied by both public L2 stations and the FCS. However, to be conservative, C_{poi} will be assumed to be relying only on FCS.

- **Step 7: Define possible locations for public charging stations**

For community demand in areas with no private home charging, the public parking spaces are the possible locations for placement of L2 charging ports. In case public parking spaces are not available, the nearest petrol station to the community is the possible location for the placement of fast charging ports. For the demand at POIs, the public places are the possible locations for placement of L2 charging outlets. These are shopping malls, metro stations, universities, parks, etc. For the fast-charging stations, the proposed possible locations are the existing petrol stations and the metro stations parking. On highways, the existing petrol stations are the possible locations. Table 5 summarizes the possible locations:

Table 5: Possible locations criteria

Demand	Possible location	Criteria
Community	Public parking space Petrol station	-
POI's	Metro stations Shopping malls Universities Parks Other public places	Established Convenient Average parking time above 30 minutes
Fast charging stations	Petrol stations Metro stations	-
Highway	Petrol stations	-

- **Step 8: Determine the required number of stations**

The following equation determines the required number of fast-charging stations to satisfy the POI demand.

$$S = \frac{Number\ of\ EVs\ \times\ Demand\ per\ EV}{Outlets\ per\ stations\ \times Outlet\ power\ (kWh) \times charging\ time\ (h)}$$

In early EV markets, it is better to limit outlets per station to 2 or 4. This increases the coverage and distribution of more stations with a lower budget. The stations, however need to have provision to add 6 to 10 more outlets as the demand increase.

The current technology managed to design charging outlets that deliver 350 kW power by solar panels (Fastned, 2019). Similarly, fast-charging stations are planned to be installed in Qatar, delivering 180 kW (The Peninsula Qatar, 2021). The charging time is the expected time the station will be working and serving customers, this could be 4-10 hours depending on the station's location, the number of customers, and their requirements. For example, users' requirements could be satisfied by a 5-minute charge delivering 15 kWh equivalent to 100 km range, or may need 15 to 20 minutes for a full charge.

- **Step 9: Facility location optimization models**

After determining the number of fast-charging stations required to satisfy the demand for public charging, the set covering facility location optimization technique and the maximum coverage facility location optimization technique will be used. These are discussed below.

The optimization criteria used here is to capture the most demand and the maximum coverage location model (MCLP) is used.

The MCLP model is as follows:

I=set of demand (Districts)

J=set of possible locations

$d_{ij} = \%\ Intersection\ between\ i\ and\ buffer\ j$

$D = Radius\ of\ coverage$

$S = number\ of\ stations\ to\ be\ established\ at\ POI's$

Decision variable:

$x_j = 1\ if\ station\ is\ established\ at\ location\ j\ ;\ \ 0\ otherwise$

$w_i = Demand\ at\ node\ i$

The Objective function for the MCLP is:

$$Max \sum_{i=1}^{n} w_i x_i$$

Subject to

$$\sum_{j=1}^{m} x_i \geq \text{S} \;\; ; \; \forall_i = 1, \dots, n$$

The SCP is used to distribute Fast charging stations with a coverage radius of 15 minutes (taken as a 2 km radius considering the traffic in urban areas). The set covering model (SCP) formulation is:

$$Min \sum_{j=1}^{m} x_i$$

$$Subject\ to: \sum_{j=1}^{m} x_i \geq 1; \; \forall_i = 1, \dots, n$$

$$Constraints: x_i = Binary \; ; \; x_i > 0$$

- **Step 10: Validate framework**

To validate the results and the coverage achieved by each model, a buffer of 2 km will be applied and the GIS overlay analysis tool will be used to measure the coverage of each station. The total covered area by the selected stations will be compared with the studt area.

CHAPTER 4: Study Area & Data Collection

This chapter explains the study area and the data collection.

4.1 Study area

Qatar's population as of March 2022 is 2.8 million; 1.3 million live in Doha and the bordering districts. The figure below presents the selected area of study, Doha, and the bordering urban districts.

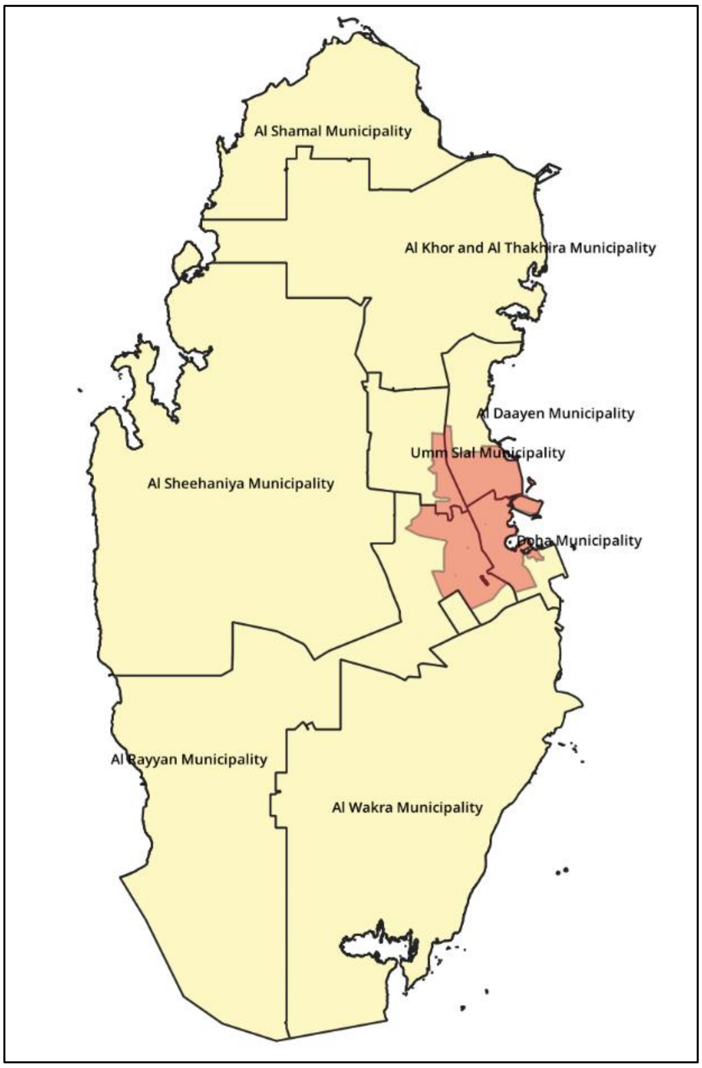

Figure 3: Study area

There are 123 districts in the highlighted area, and their size ranges between $0.1\ km^2 - 30\ km^2$. Qatar's total area is $11610 km^2$ and the selected study area is $463\ km^2$. There are currently 20 EV public charging stations.

The figure below shows the districts with more details.

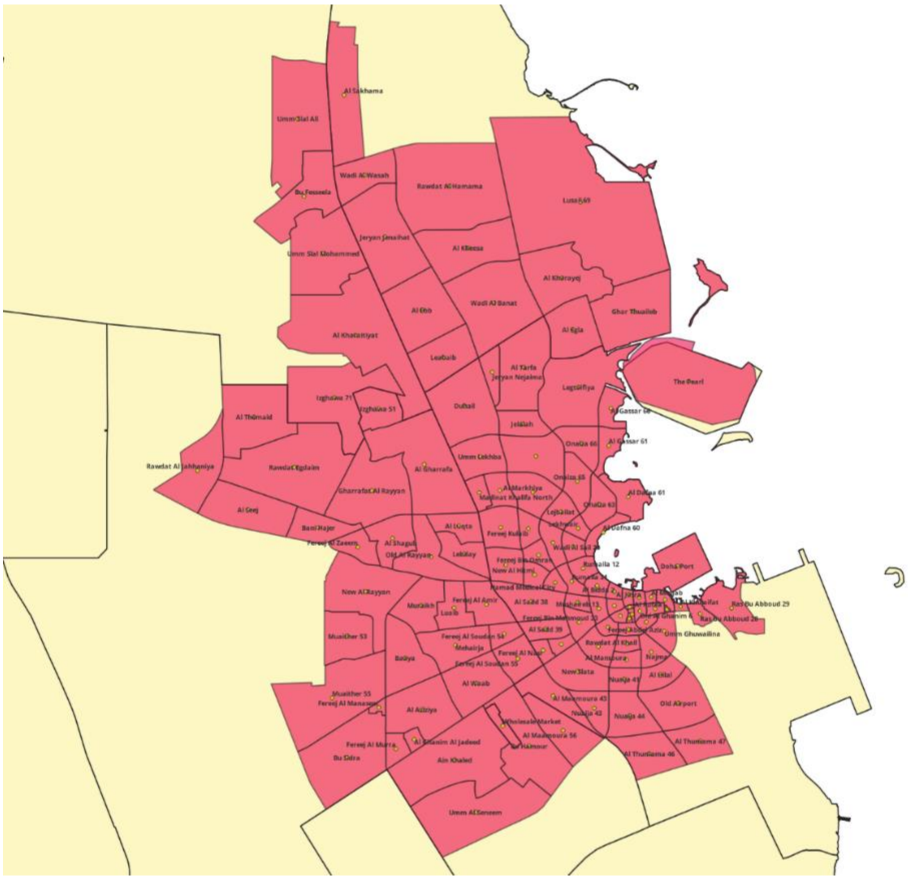

Figure 4: Districts in the study area

4.2 Data collection

This section will discuss the data collection methods used to obtain the Qatar EV market

4.2.1 Electric vehicle imports (Only Electric Motor for Propulsion)

The existing number of EVs needs to be identified to understand the demand. Table 6 below shows the number of EVs imported to Qatar from 2017 to 2021.

Table 6: EV imports (PSA, 2022)

	2017	2018	2019	2020	2021
EV imports	0	0	0	30	90
Market share (%)	0	0	0	0.1	0.2

The market share in 2020 was 0.1 % and was 0.2 % in 2021.

4.2.2 Registered new private vehicles

The scope of this research is the private vehicles such as sedans and SUVs obtained by the citizens for their private day-to-day trips. The section below explores the sales of these vehicles in the previous years. It is noted that the sales dropped in 2017 due to the blockade and dropped in 2020 due to the COVID-19 pandemic. The weighted moving average is used to forecast the sales for the following year. This gives the previous year a higher weight while considering other years. The 2020 year was not considered in the forecast. The weighting moving average forecasts 2022 sales to be 45547. This value will be used for 2023 and 2024 sales.

Table 7: Registered new private vehicles ((PSA, 2022)

Month	2017	2018	2019	2020	2021
January	4591	3919	3925	4354	3733
February	3992	3431	3445	4414	3401
March	4726	4303	4393	2999	3666
April	3848	3644	3843	1274	3079
May	4670	3696	4149	1063	3153
June	2674	2660	2941	2272	3017
July	2117	2914	3236	3233	3337
August	3255	2649	2735	2866	4658
September	2742	3381	4375	4164	5243
October	4215	4418	4609	3317	4071
November	3759	3674	4184	3337	4335
December	3300	3636	4144	3955	4524
Total	**43889**	**42325**	**45979**	**37248**	**46217**

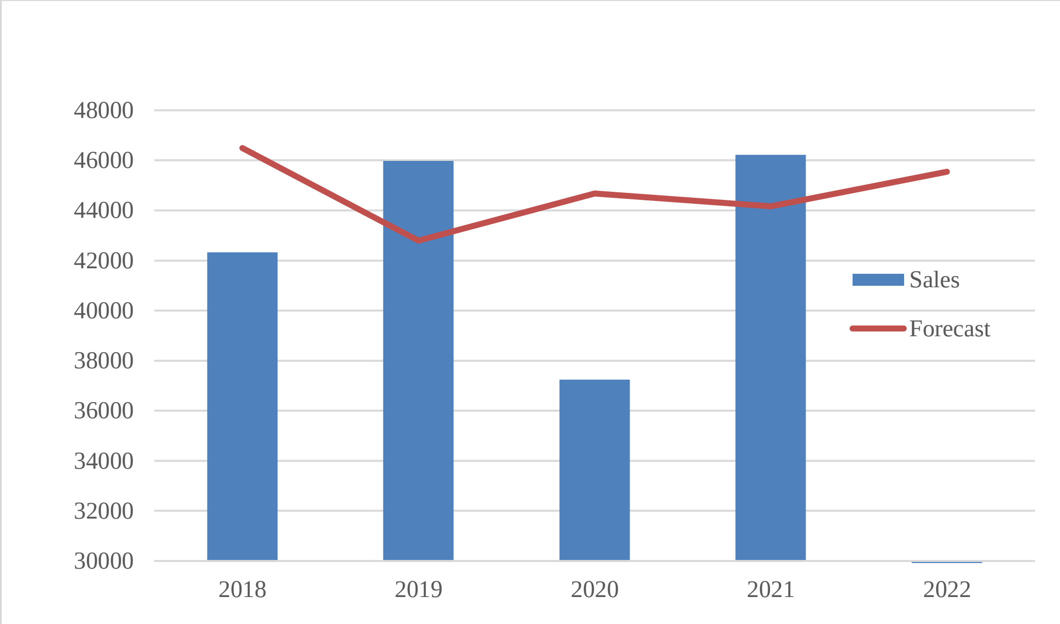

Figure 5: Registered new private vehicles

4.2.3 Global EV Market share

To better understand the EV market share, the EV market share in selected countries is analyzed below. As discussed in section 2, the uptake depends on many factors and varies between countries. Countries like Sweden and Norway increased the EV market share significantly, reaching 32% and above 50%. Other countries are still below 5%. China and Canada gradually increased the EV market share in the last five years from around 1% to around 5%.

Table 8: Global EV market share

(%)	**2016**	**2017**	**2018**	**2019**	**2020**
Japan	0.6	1	0.9	0.8	0.6
Sweden	3	5	8	11	32

(%)	2016	2017	2018	2019	2020
Canada	0.8	1	2.8	3.3	4.2
Korea	0.3	0.9	0	2.3	2.9
China	1.4	2.3	4.5	4.8	5.7
Others	0.5	1.1	1.9	1.6	1.8

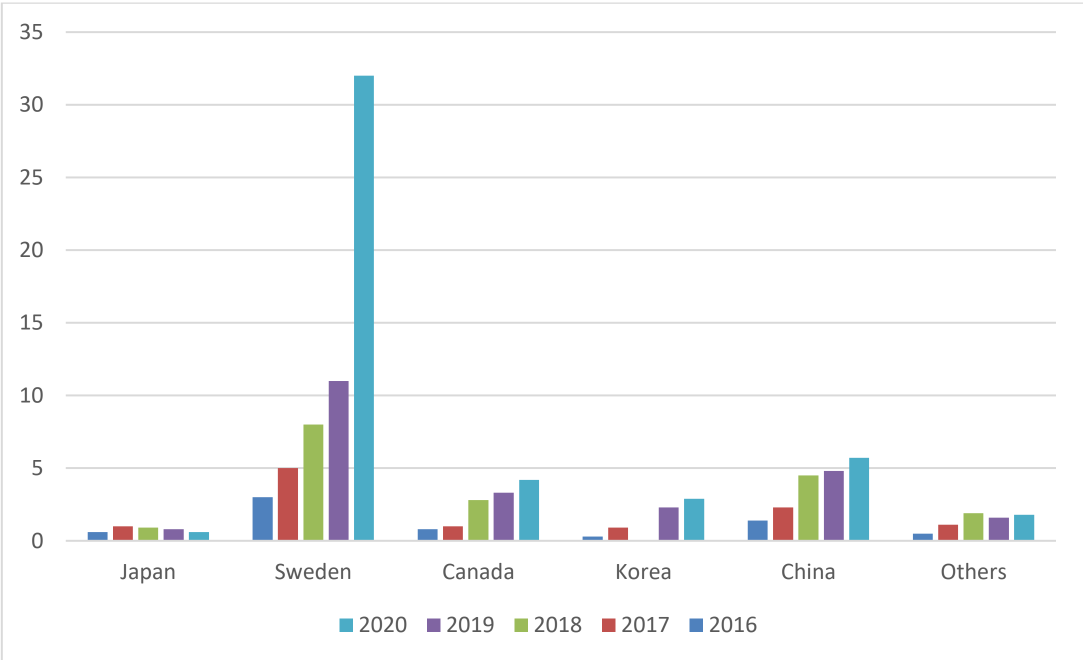

Figure 6: EV Market share in selected countries (IEA, 2021)

4.2.4 Geographic Information System (GIS)

Different GIS layers will be used to enhance the study to identify the interaction between demand points and the possible locations. First, the landmarks of the study area will be used to identify every petrol station in the districts. Then, after identifying all the possible locations, a GIS tool will be used to calculate the distance between every possible location to each demand point. Also, a buffer of 2 km will be placed on the possible locations to calculate the percentage covered in each district. The previous step of placing a buffer of 2 km will be flexible and depend on the requirements of the planning authority of the country. QGIS 3.2.2 software has been used, and the GIS layers for the districts, streets, and points of interest will be downloaded from Qatar Atlas (PSA, 2022a).

4.2.5 PTV VISUM

The PTV VISUM traffic simulation software will be used to identify the demand nodes and estimate demand at nodes. This software takes input from multiple sources to simulate the traffic in a region. In addition to other data sources, the software utilizes pneumatic tubes and ultrasonic sensors placed on many roads to measure traffic volumes reliably. Qatar Transportation and Traffic Safety Center (QTTSC) will grant access to the software to obtain the origin/destination data of Doha. The O/D matrix is available in the appendix. The figure below shows a screenshot of the software showing the traffic count of different streets.

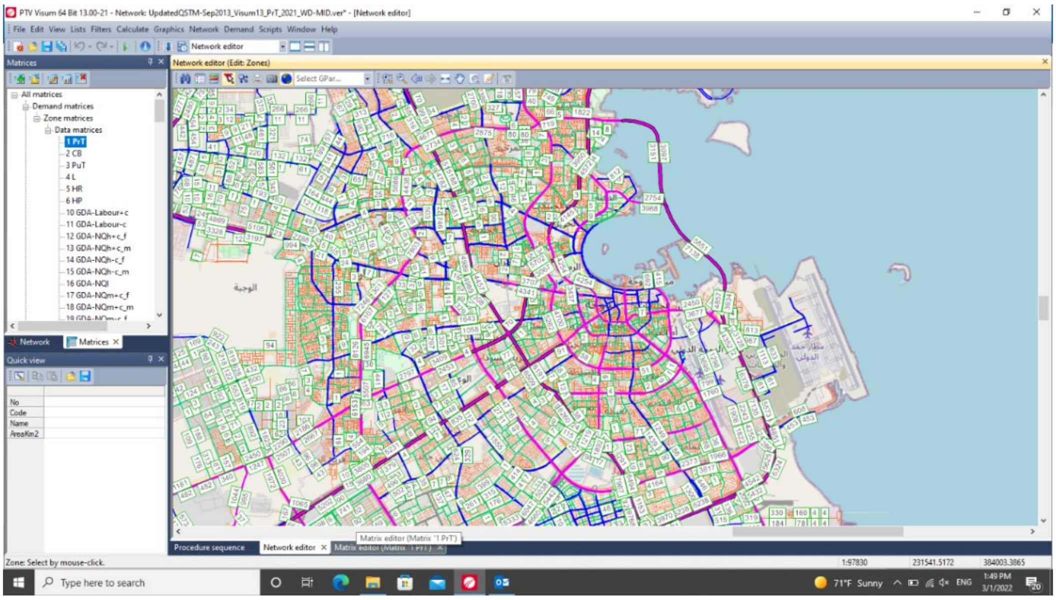

Figure 7: PTV VISUM traffic simulation software

CHAPTER 5: Results & Discussion

This chapter will discuss the results of the proposed model in the defined study area in Doha. Stage 1 of the study determined the required number of stations, discussed in section 5.1. Then, Stage 2 focused on identifying all the districts and the demand points in the chosen area. Following that, on stage 3, the researcher pointed out all the possible locations to use some of them as a new station. Then, stage 4 showed the model's core where the intersection of distracts, demand points, and possible locations was found and extracted in a matrix format obtained from GIS. Next, the matrix was used to implement the set covering the optimization model on the same stage. Next, the researcher used the same matrix obtained in stage 4 to implement the maximum coverage location optimization model (MCLP), considering demand and without a demand. Finally, stage 5 showed the validity of both models and discussed the results.

5.1 Forecast public charging demand

The number of expected EVs on the road in the next four years needs to be forecasted to forecast the demand for public charging. A scenario for EV market share in the next four years is developed based on data from Doha's actual EV market share (Table 4) and an analysis of the EV market share in selected countries (Table 6). Table 9 presents the results.

Table 9: Doha EV market share (Forecast)

Comparison	2020	2021	2022	2023	2024	2025
EV Market share (%)	0.1	0.2	0.5	1	2	4

Considering the sales of new private vehicles, the forecast for the expected EVs to be on the road by 2025 is shown in Table 10.

Table 10: Expected number of EVs

	2019	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
New private vehicles	45979	37248	46217	45547	45547	45547	45547
EV market share	0	0.1	0.2	0.5	1	2	4
Total number of Evs	0	30	90	318	773	1684	3506

To serve the 3506 EVs expected to be on road in 2025, the daily energy consumption of the EV users needs to be obtained. This was conservatively assumed in section 3, step 3 to be 30.3 kWh. This means that in 2025, Doha will need to provide 106232 kWh daily to EV users. The share of public charging could be assumed to be 40% based on reported values in the literature (Funke et al., 2019). Using Equation (4) and taking the value of 40% for the share of public charging, 42493 kWh needs to be provided daily by the public fast-charging stations.

Using this value in step 9 from section 3, the minimum number of required fast-charging stations is 20, as shown in the Equation below:

$$S = \frac{0.4\ \times 3506\ \times\ 30.3\ kWh}{2\ \times 180\ kWh \times 6} = 20$$

5.2 Demand points set up on GIS

The districts selected in this study were 123 and were presented earlier in chapter 4. The GIS layer for the districts was combined with O/D data from the VISUM software to identify the demand points. A heat map for the demand points was created to visualize areas with high demand. The figure below shows the districts and the demand points.

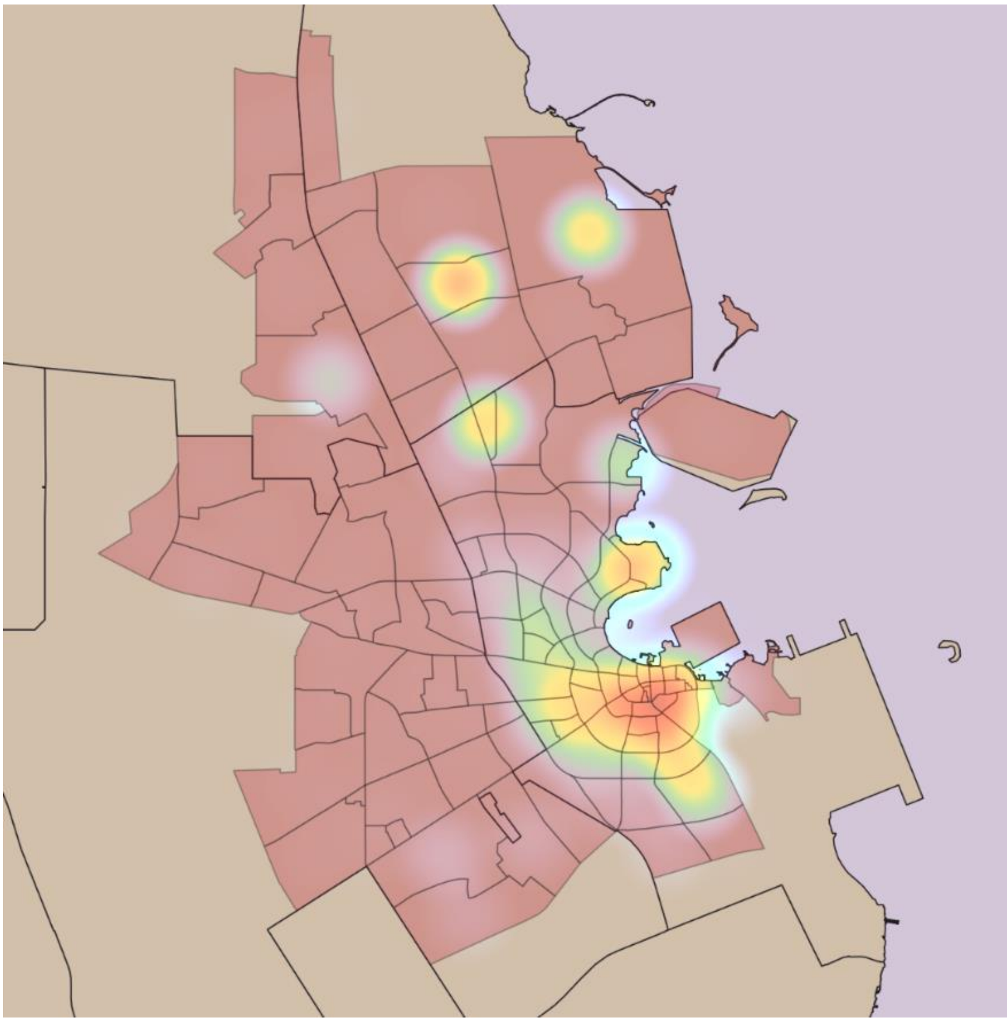

Figure 8: Demand points

5.3 Possible locations identification and set up on GIS

The proposed possible locations for this research were 65 existing petrol stations and ten metro stations with parking. These were presented as GIS layers, as shown in the figures below.

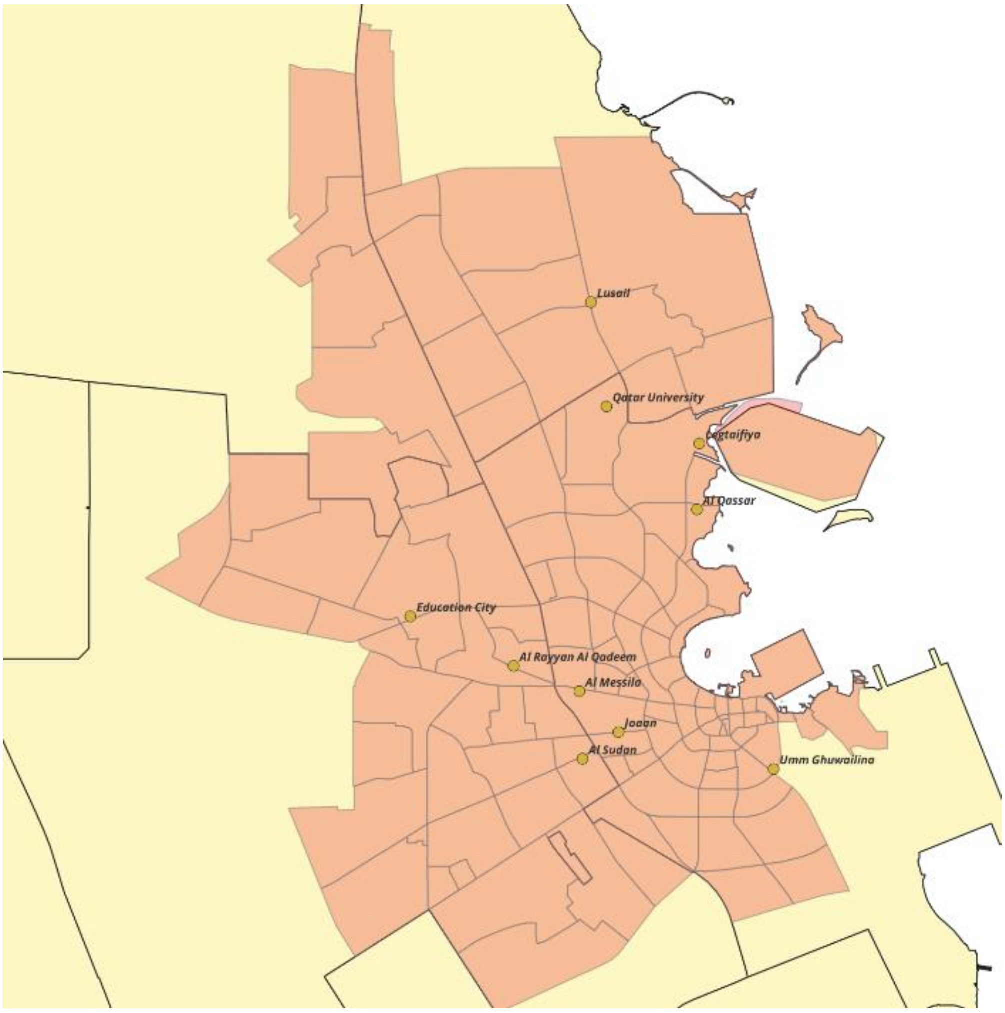

Figure 9: Possible locations (Metro park and ride)

Figure 10: Possible locations (Existing petrol stations)

Then, a buffer of 2 km on each possible location was placed, as shown in the figure below. The 2 km was meant to be a conservative representation of the 15 minutes travel time in the urban area.

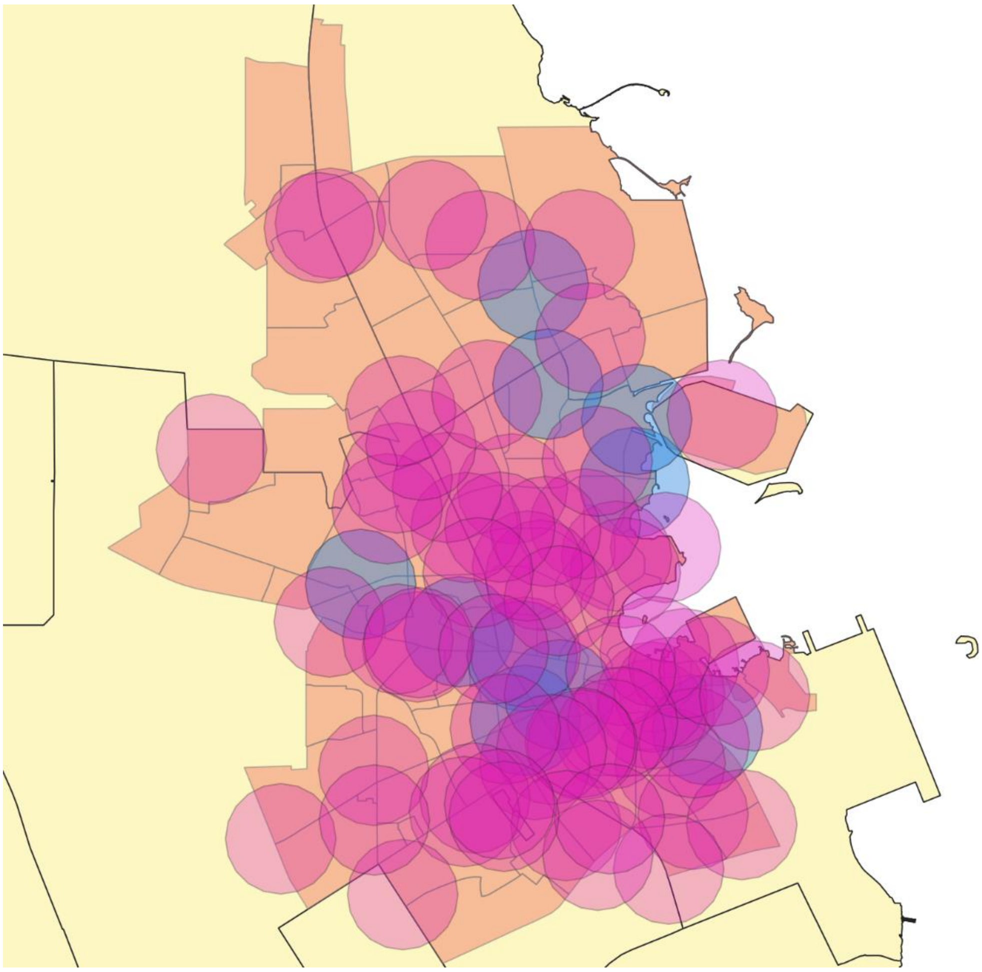

Figure 11: Buffered possible locations

5.4 Facility location optimization model

This section presents the results from the facility location optimization models.

First, the interaction between the districts and the possible locations was determined. This was done by measuring how much percentage of the districts does each possible locations cover. This was done using the *split vector layer* and *overlap analysis* GIS tools. This resulted in a 123 X 75 percentage coverage matrix. A sample of the percentage coverage matrix is presented in Table 11. From Table 11, it is noted that possible location 1 covers 98.7 percent of the Lejbailat district.

Table 11: Percentage coverage matrix

	1	6	15	27	28	29	30	31	32	33
Lejbailat	98.7	49.8	50.6	0.0	64.0	90.5	0.0	0.0	80.6	0.0
Lekhwair	99.0	0.0	0.0	0.0	0.2	100.0	0.0	0.0	100.0	0.0
Onaiza 63	4.4	0.0	0.0	0.0	36.9	100.0	0.0	0.0	100.0	0.0
Onaiza 65	4.4	0.0	44.5	0.0	100.0	98.0	0.0	0.0	73.7	0.0
Onaiza 66	0.0	0.0	5.9	0.0	97.2	28.0	0.0	0.0	4.7	0.0
Al Gassar 61	0.0	0.0	0.0	0.0	38.7	28.3	0.0	0.0	12.0	0.0
Hazm Al Markhiya	0.0	24.6	99.6	0.0	73.6	12.5	0.0	0.0	1.2	0.0
Al Hilal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.5
Old Airport	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	44.9

Then, to prepare the above matrix for the optimization model, the Table was converted to ones and zeros matrix. This was done by setting the criteria of 60% coverage, which means that if the possible location covers 60% of the district, then it is 1; otherwise, 0. Finally, the appendix shows a sample binary matrix.

5.4.1 Set covering model

By running Microsoft excel solver to solve the set covering facility location optimization model explained in chapter 3, the solution selected 37 locations to cover 60% of all possible districts within a 2 km radius. The figure below shows the results.

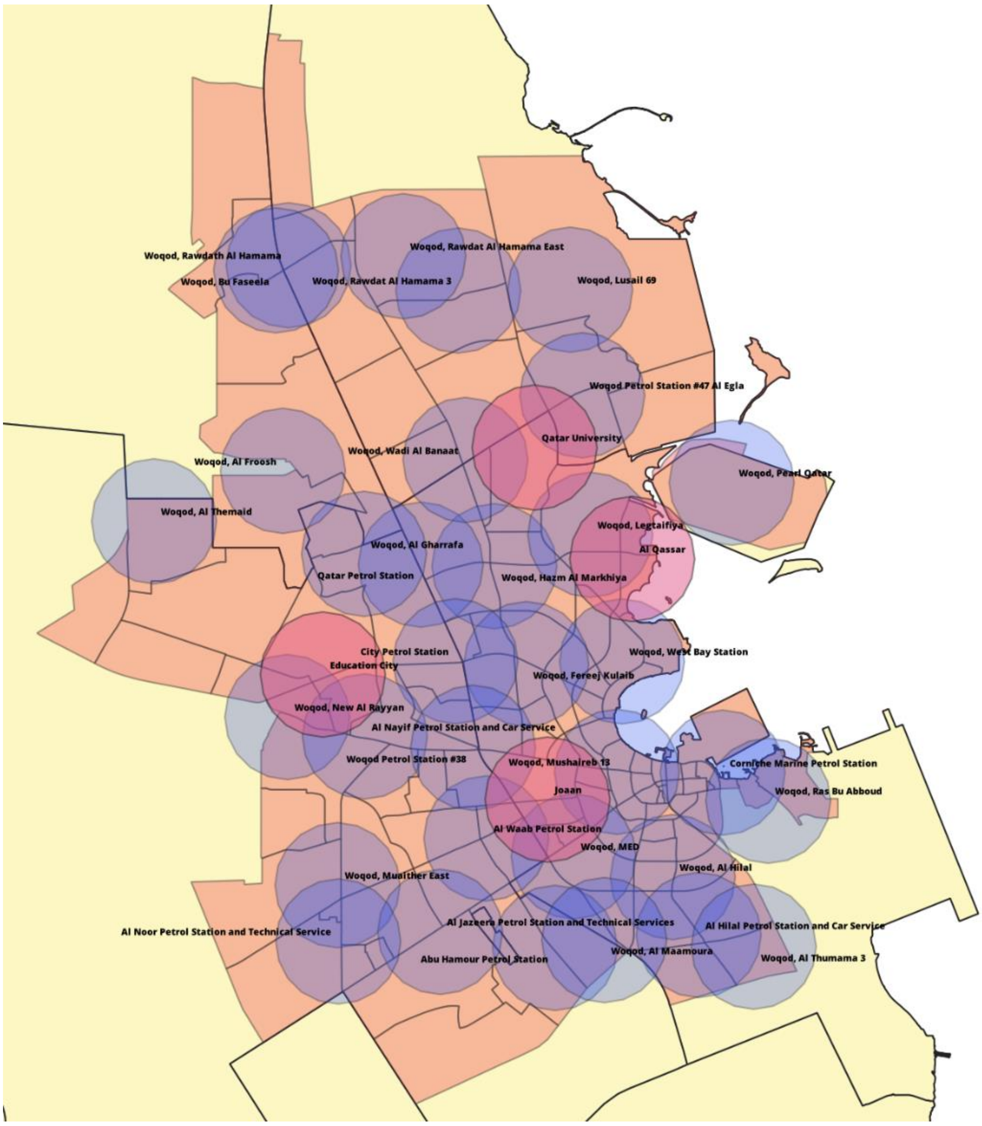

Figure 12: Set covering solution

The above-proposed solution could work well in early markets as the demand is low. This is a cost-effective solution proposing to spread the EV fast-charging outlets in the existing petrol stations instead of having them concentrated in certain areas. The energy source could be solar panels if the existing electricity infrastructure cannot accommodate it. As the demand increase and the outlets in some stations are observed to be utilized heavily, more outlets can be added.

5.4.2 Maximum coverage location model – Without demand

If the budget is insufficient to place fast-charging outlets in 37 stations, the maximum coverage location model could be used. This model had the number of stations as an input, identified earlier as 20 stations. In the first case, the demand was not considered, and the objective function was only to place 20 stations to capture most districts. The solution is presented in the figure below.

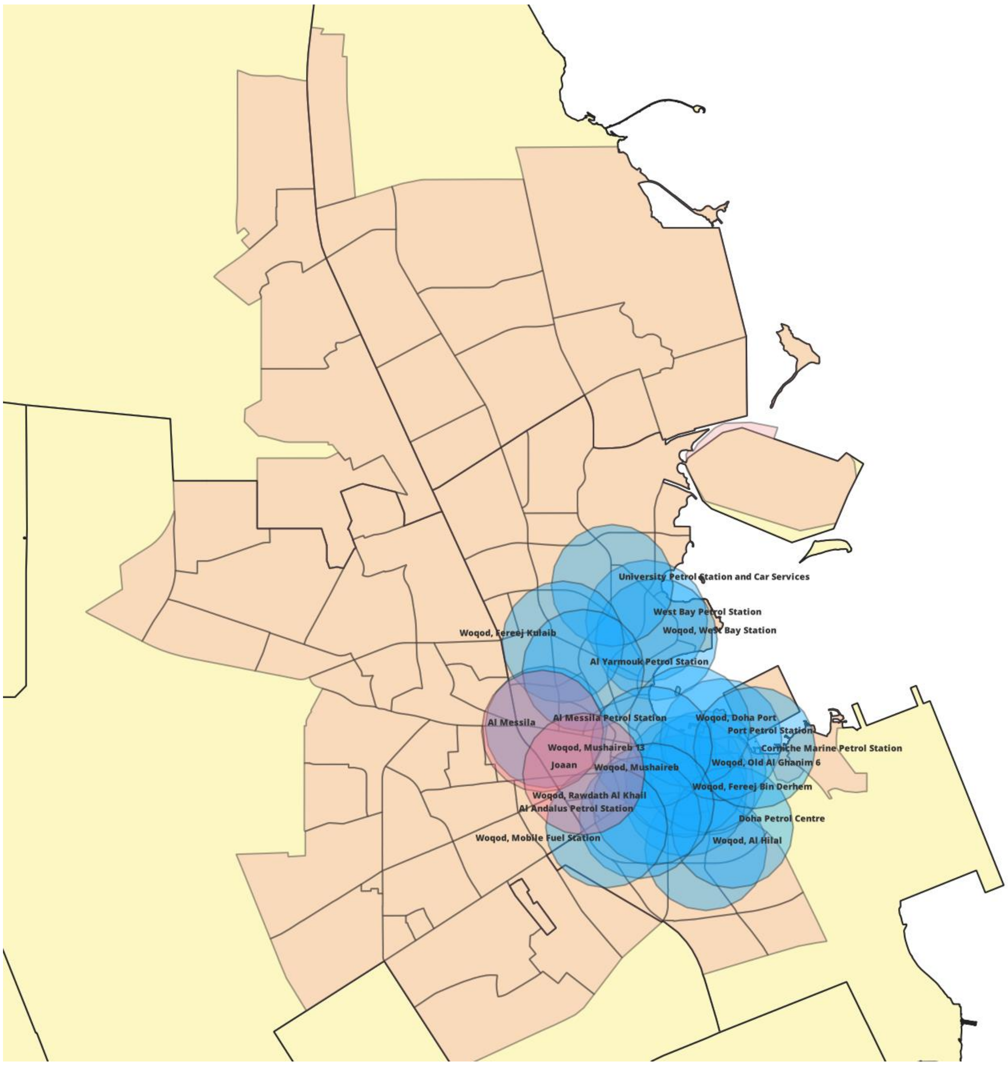

Figure 13: MCLP solution - without considering the demand

The above solution concentrated the selected stations in one area around the smaller districts. The model objective was to cover most districts with a limited number of stations, and the districts are not similar in size or density.

5.4.3 Maximum coverage location model – With demand

In this case, the maximum coverage location model was used considering the demand. Similarly, the number of stations was an input which is 20. This placed the 20 stations near the most visited destinations. The figure below presents selected stations.

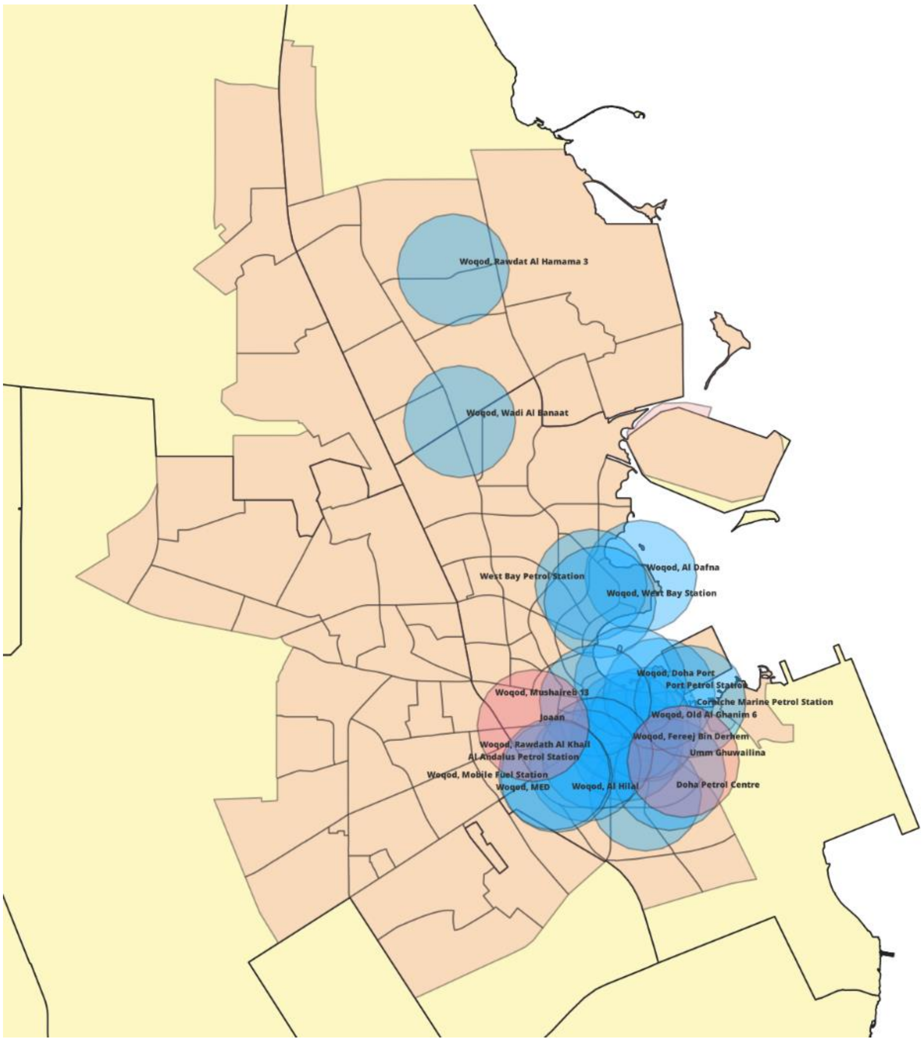

Figure 14: MCLP Solution - considering the demand

When the demand was less concentrated in a single area similar to the above solution, the resulting allocation is still considered highly concentrated in a small area. However, most demands were concentrated in a single area, which forced the model to prefer stations near the hotspots. Therefore, the O/D demand estimation approach's limitation is that the demand in one area could be a duplicate to a nearby area. This needs to be investigated further to represent demand better and remove duplications if present.

5.5 Discussion

The number of EVs expected to be on-road is 3506 by 2025. Then, the number of stations required to supply these was assessed to be 20 if two fast-charging outlets were provided at each station. The number of outlets in each station can increase up to 10 as the demand increase. This means that this approach could be reliable even if the forecasted number of EVs increases five folds to 17530 EVs on the road by 2025. The EV market share will need to increase to 10% soon for this scenario to happen. This is possible if many EV models are introduced to the market and the uptake factors are introduced.

One of the contributions of this study was to provide an accurate and reliable method to identify and estimate demand nodes as few papers considered this and relied on instead on population density data. For this, PTV VISUM software provided the traffic count and the origin/destination data between different points. These were used as the demand in the MCLP model.

The set covering model provided a solution to spread 37 stations around the city, each with 2 outlets. However, one of the restrictions with the set covering model is that not all demand points have a possible location within the critical coverage distance. In addition, the set covering model gives all demand points equal weight and does not consider areas with higher demand as more important.

To validate the results obtained from the models, step 10 was applied to measure the total covered area. The MCLP model considering the demand covered 82.9 km^2 (17.9%) of the 462 km^2 study area. When the demand was considered in the MCLP model, 78.5 km^2 (16.9 %) was only covered. In contrast, the SCP model covered 302.2 km^2 (65.2 %) of the study area as the stations were well-distributed.

CHAPTER 6: Conclusions

In conclusion, this study aimed to provide a framework to improve the demand assessment and location-allocation of public fast-charging stations. This was done in 3 main stages. The main findings of the study showed that the demand for charging is dependent on many factors, mainly the uptake of EVs, which was also found to be dependent on many factors. A scenario was assessed to determine the demand for public charging, and this resulted in 20 stations with two initial charging outlets. The number of outlets can increase as the demand increase.

The other finding was that existing petrol stations and metro stations parking were well prepared to be utilized as platforms to host EV fast charging outlets. The study used city wide traffic count data simulated in PTV VISUM software to improve the accuracy and reliability of demand. This identified areas with high traffic, which were used in the MCLP model to select locations to capture most demand. The results show that with the current districts set up, the MCLP model selects most stations in a small area only covering 17% of the study area. In contrast, the SCP model selected 37 stations to capture most area in all districts, resulting in 65.2 % coverage of the study area.

6.1 Future work

Some of the points to consider for future work are discussed in this section. First, empirical data collection could be done to validate the framework. Second, this framework assumes that all districts have an equal chance to have EV adopters. This may not necessarily be true, and further work is required to understand where are the EV adopters expected to be. The MCLP model resulted in many stations concentrated in same area, this was due to the unequal size of the districts which varied between0.1 km^2-30 km^2; future work could consider different ways to represent districts, possibly by combining number of the small districts. Another approach could be the combination of both SCP and MCLP models, as each model would cover the other's limitation. This would ensure that the entire study area is covered by at least one station, and the area with high demand has more stations. Finally, more work is required to identify and assess the demand and needs for public charging.

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APPENDIX A

PTV VISUM O/D Data

Table 12: VISUM O/D Demand data

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Aerospace City	691	2041	827	770	721	2000
Al Ghuwairiya - Al Ghuwairiya	591	348	600	690	586	504
Al Jemailiya - Al Jemailiya	135	57	119	143	131	52
Al Jemailiya - Al Nasraniya	81	81	90	78	87	171
Al Jemailiya - Al Utouriya	86	33	75	78	85	47
Al Jemailiya - Dukhan	1341	760	1413	1655	1384	1332
Al Jemailiya - Umm Bab	485	247	527	638	549	452
Al Khor - Al Khor	13239	7418	14044	16258	12957	6126
Al Khor - Al Thakhira	9278	6789	9197	10213	9838	7008
Al Rayyan - Abu Nakhla / Mukainess	728	1601	1254	765	872	2010
Al Rayyan - Al Gharrafa/Bani Hajer	5382	3558	5892	6276	5458	2846
Al Rayyan - Al Khulaifat Al Jadeed	8943	13143	11495	11006	10176	12406
Al Rayyan - Al Khulaifat Al Jadeeda/ Al/Maamoura/Abu Hamor	17491	14322	14722	16224	17328	13010
Al Rayyan - Al Luqta/Al Rayyan Al	3576	2903	4151	4494	3718	2386
Al Rayyan - Al Rayyan Al Jadeed/Mu	5272	3731	5762	5994	5454	3087

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Al Rayyan - Al Shahhniya	2329	1067	2123	2442	2230	985
Al Rayyan - Al Soudan South/Al Azi	14074	12783	15786	15433	14775	11161
Al Rayyan - Fareeq Al Amir/Muraykh	4196	2694	4681	5046	4271	2146
Al Rayyan - Industrial Area	24100	33618	27126	24523	28229	29929
Al Shamal - Abu Dhalouf/Al Zubara	72	25	63	71	69	27
Al Shamal - Fuwairit/Al Jassasiya	163	71	149	170	158	90
Al Shamal - Madinat Al Shamal/Al R	402	191	384	469	390	176
Al Wakra - Al Kharrara	10	5	10	12	9	5
Al Wakra - Al Wakra	10661	9336	13329	14543	11282	8458
Al Wakra - Al Wukair	21478	17499	22121	22523	22494	16126
Barwa Financial District	58	804	479	307	174	811
Barwa Village @ Al Wakra - Al Wukair	195	392	372	482	266	353
Bin Tawar Center Zone	139	287	263	312	186	258
Camel Race Course	17	12	33	46	18	13
City Center	616	1937	1643	1941	1095	1711
Doha - Al Asmakh	1493	2576	2051	1994	1847	2294
Doha - Al Bidda	37	14	218	361	52	8
Doha - Al Diwan	74	199	97	70	105	181

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Doha - Al Doha Al Jadeeda	1317	1556	1642	1640	1443	1392
Doha - Al Duhail	591	436	620	622	602	376
Doha - Al Duhail South	1046	892	1156	1157	1094	787
Doha - Al Ghanim Al Qadeem	3398	2174	3209	3571	3428	1655
Doha - Al Hilal	2623	7171	4562	3226	3461	7038
Doha - Al Hitmi	2133	1315	1848	2005	2113	1023
Doha - Al Jasra	295	987	854	1114	561	830
Doha - Al Khulaifat	348	570	793	976	432	445
Doha - Al Mansoura/Bin Dirhem	5555	2986	4887	5237	5425	2226
Doha - Al Markhiya	987	1327	1459	1614	1152	1159
Doha - Al Matar Al Qadeem	6286	4874	7541	8202	6488	3852
Doha - Al Messila	938	925	928	866	960	854
Doha - Al Mirqab Al Jadeed/Al Nasr	2779	3512	3578	3647	3118	3089
Doha - Al Muntazah	3391	2907	3491	3580	3522	2421
Doha - Al Najada	929	1461	1341	1605	1165	1260
Doha - Al Nuaija	2138	2734	2765	2369	2316	2746
Doha - Al Rawda	1498	1595	2099	2490	1619	1299
Doha - Al Rumeila	1316	2447	1688	1676	1570	2372

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Doha - Al Sadd	5137	6652	6718	6744	5806	5752
Doha - Al Salata	1252	5232	3113	1625	1788	5713
Doha - Al Salata Al Jadeeda /Al As	1966	3793	3243	3112	2413	3663
Doha - Bin Mahmoud	6746	6404	7390	7401	7101	5493
Doha - Bin Omran/Al Hitmi Al Jadee	3894	5253	4364	4055	4268	4877
Doha - Diplomatic District	6043	9315	7625	5783	6822	9648
Doha - Doha International Airport	6975	3919	6625	6441	6733	3283
Doha - Doha International Airport	5916	4155	6477	6283	6093	3282
Doha - Doha Port	540	1020	729	514	617	1084
Doha - Fareeq Abdul Aziz	2641	1714	2572	2860	2678	1280
Doha - Kulaib	1593	1790	1956	2024	1739	1584
Doha - Madinat Khalifa	3554	2005	3602	3624	3540	1548
Doha - Mohammed Bin Jasim	676	1546	1197	1163	909	1456
Doha - Musaimeer	784	771	1081	1109	824	718
Doha - Musheireb	2634	1922	2665	2879	2685	1517
Doha - Najma	3631	3103	3698	3772	3790	2626
Doha - New District Of Doha 60	539	5914	2845	1096	1284	6398
Doha - New District Of Doha 62	84	255	306	412	140	243

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Doha - New District Of Doha 63	2433	4115	3863	3576	2860	3850
Doha - New District Of Doha 64	422	444	547	571	468	384
Doha - New District Of Doha 65	686	504	715	703	696	430
Doha - New District Of Doha 66	5313	5531	5984	5611	5685	5126
Doha - New District Of Doha 67	1003	861	1112	1088	1038	756
Doha - New District Of Doha 69	5751	11193	9652	8321	6889	12242
Doha - New Markets	459	942	708	781	614	865
Doha - Qatar University	599	563	772	739	632	562
Doha - Ras Abu Abboud	1548	1794	1640	1429	1691	1662
Doha - Umm Ghuwailina	3648	2519	3660	4049	3739	1949
Doha - Wadi Al Sail	322	983	758	756	444	1026
Jeryan Al Batn - Abu Samra	88	39	69	86	91	37
Jeryan Al Batn - Al Karaana	244	275	278	276	253	449
Jeryan Al Batn - Rawdat Rashed	631	222	492	596	583	168
Jeryan Al Batn - Sawda Natheel	4	3	8	11	4	2
Landmark Mall-Doha - Al Duhail South	106	367	308	405	190	324
Mesaieed - Khor Al Adaid	45	12	35	36	40	10
Mesaieed - Mesaieed	13895	12705	15815	16505	14206	13680

	Origin			Destination		
	AM	MID	PM	PM	MID	AM
Mesaieed - Shaqra	218	874	569	274	346	1854
Umm Slal - Al Kheesa	13778	8995	13853	14064	13607	8145
Umm Slal - Umm Slal/Al Kharaitiyat	4405	2487	4682	5162	4426	1902

Table 13: Districts and possible locations coverage binary matrix (Sample)

Name	Al Yarmouk Petrol Station	Abu Hamour Petrol Station	Al Hilal Petrol Station and Car Service	Al Jazeera Petrol Station and Technical Services	Al Mana Petrol Station	Al Markhiyah Petrol Station	Al Messila Petrol Station	Al Nayif Petrol Station and Car Service	Al Noor Petrol Station and Technical Service	Al Waab Petrol Station	Auto Mart - Petrol Station	Woqod, Mesaimeer West	Woqod, Mushaireb
Lejbailat	1	0	0	0	0	0	0	0	0	0	0	0	0
Lekhwair	1	0	0	0	0	0	0	0	0	0	0	0	0
Al Dafna 60	0	0	0	0	0	0	0	0	0	0	0	0	0
Al Dafna 61	0	0	0	0	0	0	0	0	0	0	0	0	0
Onaiza 63	0	0	0	0	0	0	0	0	0	0	0	0	0
Onaiza 65	0	0	0	0	0	0	0	0	0	0	0	0	0
Onaiza 66	0	0	0	0	0	0	0	0	0	0	0	0	0
Al Gassar 61	0	0	0	0	0	0	0	0	0	0	0	0	0
Hazm Al Markhiya	0	0	0	0	0	0	0	0	0	0	0	0	0
Al Hilal	0	0	0	0	0	0	0	0	0	0	0	0	0
Old Airport	0	0	1	0	0	0	0	0	0	0	0	0	0
Nuaija 41	0	0	0	0	0	0	0	0	0	0	0	0	0
Nuaija 44	0	0	1	0	0	0	0	0	0	0	0	0	0
Al Thumama 47	0	0	0	0	0	0	0	0	0	0	0	0	0
Fereej Kulaib	1	0	0	0	0	1	0	0	0	0	0	0	0
Al Messila	0	0	0	0	0	0	1	0	0	0	0	0	0
Lebday	0	0	0	0	0	0	0	0	0	0	0	0	0
Al Luqta	0	0	0	0	0	0	0	0	0	0	0	0	0
Madinat Khalifa South	0	0	0	0	0	1	0	0	0	0	0	0	0
Madinat Khalifa North	0	0	0	0	0	1	0	0	0	0	1	0	0
Dahl Al Hamam	0	0	0	0	0	1	0	0	0	0	1	0	0
Al Markhiya	0	0	0	0	0	1	0	0	0	0	0	0	0