İbrahim Tümay GÜLBAHAR

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ELECTRIC VEHICLE CHARGING STATION LOCATION DECISION IN TÜRKİYE

A THESIS
SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE OF
ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis titled "Electric Vehicle Charging Station Location Decision in Türkiye" has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gül University, Graduate School of Engineering & Science.

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ACCEPTANCE AND APPROVAL

M.Sc. thesis titled "Electric Vehicle Charging Station Location Decision in Türkiye" and prepared by İbrahim Tümay GÜLBAHAR has been accepted by the jury in the Industrial Engineering Program at Abdullah Gül University, Graduate School of Engineering & Science.

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ABSTRACT

ELECTRIC VEHICLE CHARGING STATION LOCATION DECISION IN TÜRKİYE

İbrahim Tümay GÜLBAHAR
MSc. in Industrial Engineering
Advisor: Assist. Prof. Dr. Muhammed SÜTÇÜ

January 2023

Electric vehicles are now regarded as one of the best and greenest replacements for internal combustion engine vehicles. For the widespread use of electric vehicles, the construction of the vehicle charging network and, in particular, the choice of the appropriate site for the charging stations, are viewed as critical issues. The majority of studies on the topic concentrate on well-known locations like city centers, shopping malls, and airports. Because there are so many alternative charging stations, even though these and comparable locations are regularly used in everyday life, they can usually provide an appropriate solution to the daily charging need. For intercity travel, it is impossible to find enough charging stations, especially on highways. To choose the position of electric vehicle charging stations on highways, a decision model has been suggested in this study. The anticipated number of electric vehicles in Türkiye over the next few years is projected in order to acquire a realistic approach to the location of charging stations, and this amount is employed as a significant input in the facility positioning model. The best places for charging stations on state highways that can meet customer demand were then identified using an optimization technique. The suggested model selects the most suitable locations for charging stations and the number of chargers that should be installed there while also making sure that drivers of electric vehicles on highways don't run into charging issues.

Keywords: Electric Vehicle, Charging Station, Time Series Analysis, Facility Location

ÖZET

TÜRKİYE'DE ELEKTRİKLİ ARAÇ SARJ İSTASYONU LOKASYONU BELİRLEME

İbrahim Tümay GÜLBAHAR
Endüstri Mühendisliği
Tez Yöneticisi: Dr. Öğr. Üyesi Muhammed SÜTÇÜ

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Günümüzde elektrikli araçlar, içten yanmalı motorlu araçlara en uygun ve çevreci alternatiflerden biri olarak görülmekte. Ancak, elektrikli araçların yaygınlaşması için araç şarj ağının oluşturulması ve özellikle şarj istasyonlarının en iyi yer seçimi önemli bir başlık olarak görülmektedir. Konu ile alakalı olarak yapılan çalışmaların büyük bir kısmı şehir merkezleri, alışveriş bölgeleri ve havaalanları gibi popüler destinasyonlara odaklanmaktadır. Bu ve benzeri alanlar günlük hayatta sıklıkla kullanılsa da alternatif şarj istasyonlarının sayısı nedeniyle genellikle günlük şarj ihtiyacına yeterli bir çözüm sunabilmektedir. Ancak şehirlerarası yolculuklarda, özellikle otoyollarda yeterli şarj istasyonu bulmak mümkün değildir. Bu çalışmada, karayollarında elektrikli araç şarj istasyonlarının yerinin belirlenmesine yönelik bir karar modeli önerilmiştir. Şarj istasyonlarının yerleştirilmesine gerçekçi bir yaklaşım elde etmek için, Türkiye'de önümüzdeki birkaç yıl içinde yollara çıkacak elektrikli araç sayısı tahmin edilmiş ve bu sayı tesis konumlandırma modelinde önemli bir girdi olarak kullanılmıştır. Daha sonra devlet otoyolları üzerinde müşteri taleplerini karşılayabilecek şarj istasyonları için optimum konumların belirlenmesine yönelik bir optimizasyon modeli oluşturulmuştur. Önerilen model, otoyollarda elektrikli araçlarıyla seyahat eden yolcuların şarj sorunu yaşamamasını sağlarken karşılaşılacak maliyetleri de göz önünde bulundurarak optimum şarj istasyonu alanlarını ve bu alanlardaki şarj cihazı sayısını belirlemektedir.

Anahtar kelimeler: Elektrikli Araç, Şarj İstasyonu, Zaman Serisi Analizi, Tesis Lokasyonu

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
AHP	Analytical Hierarchy Process
ARDL	Autoregressive Distributed Lag
ARIMA	Autoregressive Integrated Moving Average
BEV	Battery Electric Vehicle
BHFP	Bottom Hole Filtration Pressure
COP26	United Nations Climate Change Conference
ETS	Exponential Smoothing
EV	Electric Vehicle
GAMS	General Algebraic Modeling System
GDP	Gross Domestic Product
GIS	Geographic Information System
GLM	Generalized Linear Model
GLS	Generalized Least Squares
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
PHEV	Plug-In Hybrid Electric Vehicle
RFR	Random Forest Regressor
RMSE	Root Mean Squared Error
sMAPE	Symmetric Mean Absolute Percentage Error
SoC	State of Charge
TOGG	Türkiye’s Automobile Joint Venture Group
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VAR	Vector Autoregression

To My Family

Chapter 1

Introduction

People prefer to use a wide variety of tools to make everyday life easier. From the first human to nowadays, people have used many things such as their feet, domestic horses, and bicycles to move from one location to another for different reasons like finding food, meeting with someone, doing business and so forth. However, in the last two centuries, more technological means of transportation have been invented and the popularity of fast transportation is increased rapidly. One of these means of transportation is the traditional fossil fuel-dependent cars, which are used in many areas.

The technology of internal combustion engine vehicles that have been on the streets since the 19th century, which we have been using almost every day of our lives, is developing day by day and the number of uses is constantly increasing with an exponential acceleration. However, with the effect of air pollution and global warming, the place of vehicles using fossil fuels in our lives is questioned [1], [2]. According to The World Bank, as of 2014, transportation has more than 20% proportion of CO_2 emission in the world [3]. These adverse situations brought different opportunities, one of which is the increase in alternative energy vehicle usage trend [4]. As examples to this trend Figures 1 and 2 are shared below. This trend not only increased vehicle sales, but also accelerated the development of the necessary infrastructure and by-products. For more sustainable energy usage in transportation industry, vehicles that energized with alternative-fuel, especially electric vehicles (EVs), are seen more logical and suitable way [5]. Therefore, studies are analysis on necessary infrastructure for EVs became one of the main topics of related conversations.

The most important infrastructure requirement is undoubtedly charging stations in order to provide the maintenance and support of electric vehicles. However, it is important to understand that the infrastructure has just begun to be established, therefore the priorities and requirements are needed to be determined and an action plan must be created to effectively use limited resources in order to satisfy the customers using EVs. One of the main limitations of EV users is having lack of charging stations which barrier to alternative fuel vehicles popularity [6], [7], [8]. To have an effective and useful plan for determining charging station locations, several cases from different aspects are analyzed and various methods hold out and those studies are discussed under the literature review

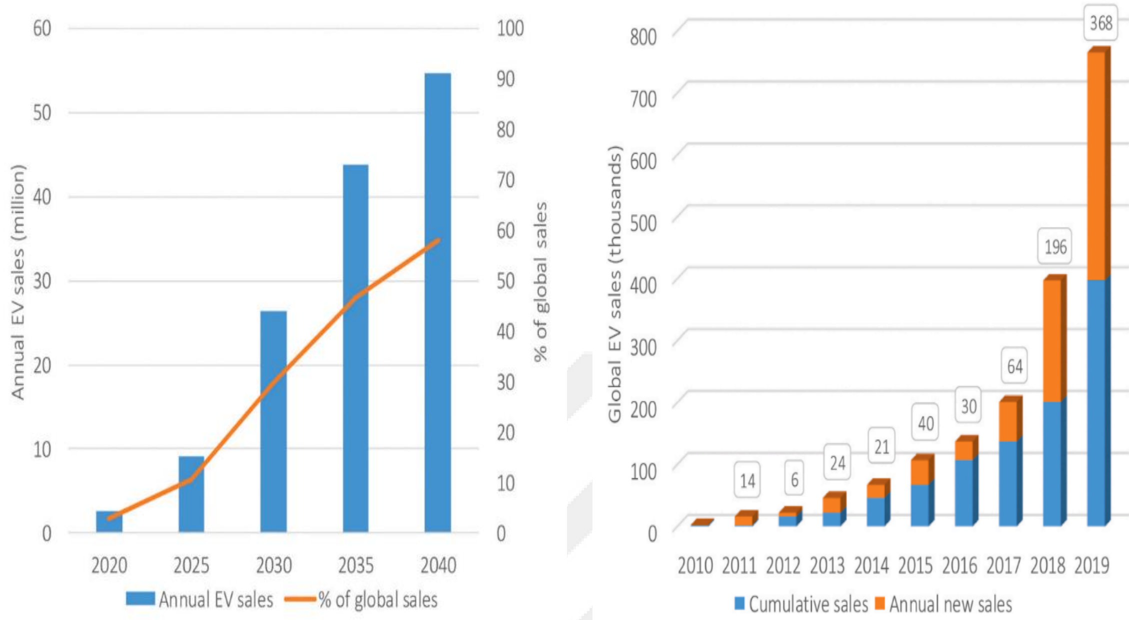

Figure 1.1 EV Sales Forecast and Global EV Sales (Adopted From [85]**)**

section.

The problem investigated in this study is not just a theoretically created problem but also a globally discussed affair as mentioned. This widespread issue is taking place in actions of companies working on related industries, non-governmental organizations, even statesmen of the countries. At the end of 2021, Scotland hosted the United Nations Climate Change Conference (COP26) between the 31st of October and the 12th of November. The main issue discussed in these conferences was the climate change and the global warming. Declaration about the zero emission cars and vans till 2035 is signed by 33 countries, 40 cities, 11 automotive manufacturers and 27 fleet owners [9]. Türkiye was the one of those countries that signed this declaration.

One another motivation of this study is that the investment of TOGG (Türkiye's Automobile Joint Venture Group) on the EV technology and manufacturing in Türkiye. The manufacturing process is expected to start in 2022 [10]. Therefore, burst of demand will be observed for the charging station in the region. On the other hand, there exist not much study on this topic that covers possible optimum locations for charging stations in

Türkiye especially on highways. This study offers optimum locations for the charging stations that can meet the customer demands on the given highway.

The use of electric vehicles in Türkiye is increasing exponentially. Especially, considering the TOGG investment and the agreement Türkiye signed to shut down manufacturing diesel and gasoline vehicles in Türkiye by 2035, providing the infrastructure of EVs, which is the main motivation on this study, is of great importance. Thus, based on the future progress on electric cars in Türkiye, a suitable and environmentally friendly model is needed to build proper infrastructure for the electric vehicle.

To be able to specify the optimal quantity and location of charging stations for the best level of customer satisfactory, the number of EVs that will exist on the related regions should be taken into consideration. However, future number of the EVs in Türkiye is unknown and there exist no academic studies conducted on this field. Therefore, the number of EVs will hit the road in next several years must be analytically estimated, which is also handled in this study. The results, the number of EVs, will give a brief information about the demand level of the future customer and provide a base for the best locations determination. Consequently, the number of EVs on the road, the needed charging station numbers and their locations are going to be analytically offered.

On the other hand, while analyzing the number and locations, application area must be specified. During ordinary daily life, people can usually provide an adequate solution for their daily charging needs due to the number of alternative charging stations in urban areas and the range that they travel is limited. However, when traveling between cities far from each other, considering the distance to be traveled, it is not possible for electric vehicles to complete their travel with a single charge. Electric vehicle battery technology currently has an average range of 340 km [11]. For this reason, vehicles may need to be fully charged twice for a trip of approximately 450 km, such as from İstanbul to Ankara. For this reason, distance covered by an EV should be considered while establishment of the charging stations.

All in all, the aim of this study is to introduce a novel approach which offers charging station locations and needed number of chargers on them. The contribution of this study to the related literature is to optimally decide the charging stations locations that can meet the customer demands while estimating the number of EVs for the near future.

1.1 Electric Vehicle

In this section, basic information about development and spreading of electric vehicles thorough time and types of electric vehicles will be given under two subsections in order to inform readers about basic concepts of electric vehicles.

1.1.1 History of Electric Vehicles

More than 150 years ago, with a series of breakthroughs from batteries to electric motors, the technology of electric vehicles emerged. Robert Anderson, a British inventor, built the first crude electric vehicle around 1832, but there were no practical examples of this new system until the second half of the 19th century. After 1870s, some of first practical examples of electric cars were built by British and French inventors [12].

Although electric cars had a great success against the steam or gasoline powered cars for quite some time since they were easier and more comfortable to use due to the alternatives being in need of muscle power even to start the car and operate, having a disturbing exhaust and loud noise; after Charles Kettering eliminating the need to hand cranks to start the gasoline powered cars by introducing electric starters in 1912 and electric vehicles costing nearly three times a gasoline powered car, their popularity started to diminish. After the discovery of crude oil in Texas, gas became cheaper and spread faster than electricity around USA which made electric vehicles obsolete by 1935. In mid-1970s several incidents brought electric vehicles back to market but some drawbacks they had compared to combustion engine cars such as range and lower performance did not let them rise [12].

Until the late 20th century, this situation of electric vehicles being costly to produce and the combustion engine cars dominating the market continued. Later, with the needed advancements in essential technologies (such as efficient and easily rechargeable batteries with high capacity) and the recent environmental concerns (such as global warming) which directed the world away from fossil fuels into renewable energy, electric vehicles became more popular and usable. Around mid-1990s several big car manufacturers released their hybrid vehicles (which uses both an electric and a combustion engine) and succeeded in spite of combustion engine cars domination on market. In early 2000s battery electric vehicles started to take their place in the market [12].

1.1.2 Types of Electric Vehicles

In this part, types of electric vehicles will be mentioned under subsections. There are different types of electric vehicles, however these sections will be focused on externally rechargeable types of vehicles.

1.1.2.1 Battery Electric Vehicles

Battery electric vehicles (BEVs) are the type of vehicles that do not contain a combustion engine and are powered by an electric motor which uses only a battery (usually a Li-ion battery) as its energy source. Batteries of these vehicles can be recharged externally by plugging in a charging station or simply a power outlet.

BEVs usually are high efficiency cars with zero tailpipe emission which exterminates the environmental concerns for users [13], [14]. Recently, this encouraged many car manufacturers to promise changing their entire production line from combustion engine vehicles to BEVs until 2050 (Rolls Royce, Ferrari, Volkswagen, Citroen: 2030, Honda: 2050) [15].

Since there is only one way to empower the BEV, one of the crucially important parameters is distance coverage of the model. Range also is another parameter for customers to make decision on whether to buy it or not. In the recent models, ranges differ between 95 (Smart EQ Fortwo Cabrio) to 695 (Lucid Air Dream Edition R) kilometers which is a huge interval [11]. However, with the purpose of the customer to buy one of those, any model of BEV can be appropriate to afford.

1.1.2.2 Hybrid Electric Vehicles

Hybrid electric vehicles carry two different engines, one being an internal combustion engine and other being an electric motor. There are two types of hybrid electric vehicles; the first type is the one that cannot be recharged externally (will be addressed as HEVs) and the second type has plug-in recharge feature (will be addressed as PHEVs).

The first type of hybrid electric vehicles has both a combustion engine and an electric motor. This type of vehicles is dependent on fossil fuel since their batteries are not externally rechargeable. HEVs recharge their batteries by using technologies such as regenerative breaking and they utilize idle-off. There are series and parallel types of HEVs. Series type HEVs are more efficient for frequent stops while parallel type HEVs are more efficient for cruising at a stable speed. Thus, series types provide fuel save in-city driving while parallel types consume less fuel in highway drives [16], [17].

The second type of hybrid electric cars also has both a combustion engine and an electric motor [18], however PHEVs do not depend on fossil fuel for they are possess externally rechargeable batteries by plugging to a power socket [19]. PHEVs can be considered as externally chargeable versions of HEVs and in addition they have longer range due to larger battery and being able to save even more fuel since they are more flexible on power source being independent of fossil fuels [20]. PHEVs also use technologies such as regenerative breaking to recharge its battery while on cruise [16].

1.2 Thesis Structure

The remainder of the thesis structured as follows.

In "Chapter 2" the problem is stated, and related literature is reviewed. Literature review is divided into two sub-sections as the forecasting approaches and the mathematical modelling approaches for location problem. In the first sub-section, forecasting techniques, used in this study, are investigated. In the second sub-section, studies about the optimum location selection are examined.

In "Chapter 3" data structure used for the forecasting approaches is explained. In addition, definitions and explanations about the application methods of the used approaches are made and the evaluation metrics are presented.

In "Chapter 4" there exist two main sections as method application and the results. At the beginning of each applied methodology data gathering and preprocessing procedure is represented. After data gathering and preprocessing, a novel approach for estimating the future number of EVs by using existing time series analysis method is introduced, and the formulation of mathematical model that offers the optimum numbers and places for the charging stations is covered. Also, results of the analyses are shared. The output of the forecasting approach and the error rates of those are given. Last but not least, the suggested quantity and location of charging stations, as output of the mathematical model, are specified.

In "Chapter 5" a summary with discussion of the Societal Impact and Contribution to Global Sustainability of the thesis is given. Chapter concluded with the further direction in the related research area.

Chapter 2

Research Background

This chapter consist of two sections which are the problem statement and the literature review. In the first section, an extensive definition of the problem is stated. In the second section, related literature is investigated, and studies are briefly explained.

2.1 Problem Statement

Today, the rate of development in technological fields is very high. However, in order for these developments to take place in our daily lives, certain conditions must be met. Along with emerging technologies, the development of the related infrastructures required by these technologies is one of the most important conditions. Nowadays, electric vehicles have become widespread, one of the first conditions for the increase in usage and for individuals to adapt to this process more easily is the installation of a charging station.
Due to the short distance trips in urban transportation and the easy access to charging, the preference of electric vehicles for inner-city use is increasing. However, since long distances are involved in intercity transportation, it is often not possible to complete the journey with a single charge. For this reason, charging stations should be located on highways in order to spread the use of electric vehicles in intercity transportation.
Intuitive positioning of charging stations is not a suitable method for both users and charging service providers. In this process, the main purpose should be to reach the highest satisfaction of both stakeholders.
The necessary condition for users to be satisfied is that they can charge their EVs when they need it. Otherwise, the electric vehicle will be stranded on the highway and this will bring various problems. Some of these problems can be stated as follows; running out of charge of the vehicle on the highway may cause safety problems, taking the vehicle left on the highway to the charging station means an additional cost, the life of a fully discharged battery becomes shorter than usual and so on.

From the point of view of the charging service provider, each charging station to be located has various costs. These can be listed as the cost of the placement of stations, providing the necessary electricity and transformer infrastructure, the cost of each charger and so forth. All in all, there are many important aspects to consider. This study is carried out taking into account the factors aforementioned.

In order to realize the study, a structure consisting of several steps should be established. To determine the optimum locations of charging stations required for electric vehicles, the primary need is to know the number of EVs. Since the future is unknown, the first step is undoubtedly to estimate the number of EVs that will hit the roads in the coming years. In the next step, the locations of the charging stations should be determined based on the number of EVs expected.

In interest of this study to be completed successfully, first of all, the studies in the international literature were examined and given in the next section. In the following chapters, the approaches to solve the stated problems and their results are shared.

2.2 The Literature Review

The solution approaches in this study are consist of two main categories as estimating the number of EVs in the near future and optimizing the locations of EV charging stations. Therefore, related literature investigated will be given accordingly in the following two subsections. On the other hand, for better understanding of the situation broadly, the global studies about EV are presented.

2.3.1 Forecasting Techniques

Knowing or having some idea about the future is always attractive. However, it is important to have a scientific base for those prediction. There exist so many methods to predict future of a situation in the literature. Therefore, in the following parts, several techniques used to forecast future in a given situation is examined.

A study about stock market development and economic growth in Pakistan, ARDL was used in order to investigate long-run casual linkages and short-run dynamics on an annual time series of 36 years from 1971 to 2006. After finding the integrating order and applying ARDL, they found indicators of existence of a bi-directional long-run relationship between stock market development and economic growth of the country. On the other hand, ARDL returned results for the short-run relationship implying that in short-term causality is only one-way from stock market's development to economic growth [21].

Another study published is about long-run demand for money in Hong Kong with the application of ARDL model using quarterly time series data over the period of 1985-1999. They identified a long-run relationship between real broad money aggregate, real income, nominal interest rates, foreign interest rates, and foreign exchange rates [22].

In research about household electric consumption, researchers used ARIMA on a time series of nearly 4 years and tried to analyze it daily, weekly monthly and quarterly. After they preprocessed the data dealing the missing values and forming it into an applicable format, they built their ARIMA models and chose the best models amongst them according to RMSE values which were ARIMA (3, 1, 3), ARIMA (1, 0, 1), ARIMA (0, 0, 0), ARIMA (0, 0, 0) for daily, weekly, monthly, and quarterly series respectively [23].

Another article written by Kobiela et al. used ARIMA and LSTM on NASDAQ stock exchange data to predict average stock prices for daily, monthly, 3 months and 9 months of times. After conducting necessary tests and building models, they used MSE and MAPE to choose better models. According to these error values, they found out ARIMA performed better then LSTM except daily prices [24].

For forecasting Covid-19 parameters in different countries a study was done by Larabi-Marie-Sainte et al. using exponential smoothing (ETS) and other forecasting methods such as LSTM. They conducted necessary tests for time series analysis and then they built models with ETS and other methods. They chose better models according to RMSE and validated the best models by RMSE, MAE and MSE. In this study, after all these processes, ETS performed the best [25].

In another study, Dong et al. used extends of exponential smoothing on short-term solar irradiance forecasting. They used Fourier trend model to obtain stationarity and applied an exponential smoothing model. They compared models using normalized RMSE and according to theirs results, exponential smoothing returned well outputs with the best RMSE values in their research [26].

In a time series study focusing on air pollution is prepared using Generalized Linear Models with the interest of estimating the relative risk of cardiopulmonary hospital admissions, they used a GLM and a GLMM (Generalized Linear Mixed Models, an extend of GLM) with Natural Cubic Spine in their simulation for this purpose. From the models they built, they picked the ones with the lowest AIC values considering them being the best. After this process, they checked RMSE values for GLM-NS and GLMM-NS models and they obtained lower RMSE values for their GLM-NS model [27].

Estimating the role of meteorological factors on Covid-19 spread in Africa is another study by using GLM is done by Osman. Researcher used GLM for this purpose and built different models for different countries and checked their statistical significance. They found that the GLMs they conducted were significant and regarding the temperature and humidity in those countries, varying results about the link between temperature and humidity were obtained. This study reveals that the relation between spreading of Covid-19 and meteorological factors is debatable since the effects of such factors are changing for different countries [28].

A study on operational method for determining bottom hole pressure in mechanized oil producing wells was prepared in order to introduce a statistical method such as multivariate regression analysis instead of analytical approaches to the subject. These analytical techniques were not applied in this study since their low accuracy levels, thus Ponomareva proposed multivariate regression which seems expedient for determining bottomhole filtration pressure (BHFP). They found out that although it has limitations for such field, multivariate regression was able to determine BHFP in practice and it is more functional [29].

Another approach which is about the impact of energy consumption and economic growth in some Middle East and North Africa countries (namely Algeria, Bahrain, Iran, Kuwait, Oman, Qatar, and Saudi Arabia) on CO_2 emissions over the period 1995-2014 introduced by Ardakani and Seyedaliakbar. They utilized a multivariate regression model to determine this relationship with an Environmental Kuznet's Curve (EKC). After they conducted necessary tests, they found that the countries that passed their turning point for economic growth in the means of GDP (Gross Domestic Product), multivariate regression shows that economic growth lowers the CO_2 emissions. On the other hand, the analysis implies that the countries below their turning points are increasing their CO_2 emissions [30].

2.3.2 Charging Station Deployment Techniques

The only way to increase EV drivers' service satisfaction is not to place new charging stations, but the regulate the schedules and places of the charging stations is a proper way to observe more satisfaction [31]. To be able to deal with that, waiting times are analyzed and revision of the locations of the charging stations is offered by Qin and Zhang, 2011 [31]. On the other hand, having broad service network is inevitable and sine qua non for the EV industry founders and customers. Therefore, in the literature new studies are seen frequently like implementation offerings in South Korea. One of the dramatic technological improvements still being observed in the South Korea, and that leads to EV network's proliferation. That give a raise to studies that focuses on to locating new EV charging stations like conducted case study by Chung and Kwon, 2015 [8]. They proposed a case study based on the actual traffic flow data of the Korean Expressway network. Three different methods are used to offer solution and comparison as multi-rotation optimization, forward myopic and backward myopic optimization. At the end, outcomes of the multi-rotation optimization model were observed as the most suitable method for large scale network problems.

Considering the traffic density and the capacity of the charging stations, another alternative study was conducted to reduce the time lost by electric vehicle drivers while reaching the charging stations [32]. The region is divided into nine different sub-regions using the Genetic Algorithm to find the best locations and successfully propose a solution to satisfy customers own an EV.

Another approach to deal with charging station siting problem is proposed by Erbaş et al., 2018 [33]. The approach in this study is Geographic Information System (GIS) based Multi Criteria Decision Analysis to choose places to implant charging stations. For criteria prioritization fuzzy analytical hierarchy process (AHP), for ranking between potential places technique for order preference by similarity to ideal solution (TOPSIS) are used. These approaches are applied for the inner-city of Ankara, and alternative site places are suggested as the result of the study.

Chapter 3

Approaches, Evaluation Metrics and Data Structure

At the beginning of this chapter, data structure is shared and then the evaluation metrics used for analyses are introduced. In the next sub-section, a novel approach is proposed for time series analysis by using existing algorithms. Lastly, the model for location selection and determining the number of chargers in the selected station is formulated.

3.1 Data Structure

The first step of the analysis in this study is to predict the number of EVs for next years. For this reason, several time series analyses are done. However, for better understanding and evaluation of the results, datasets used must be introduced. Since the novelty of forecasting approach does not come from the used models but comes from the way they are used, there exist two different datasets to use for estimating the number of EVs. For the first dataset, whole number of sales of passenger cars are gathered and a sample is shared in the below Table 3.1.

Table 3.1 A Sample of Passenger Car Sales Data

Date	Passenger Car Sales
2011-01	44892
2011-02	58663
2011-03	78403
2011-04	77695
2011-05	80646
2011-06	81573

On the other hand, a sine qua non input for this study is the number of EVs sold in Türkiye. Therefore, this data is gathered and in the Table 3.2 a sample is shared.

Table 3.2 A Sample of Electric Vehicle Sales Data

Date	EV Sales
2018-01	10
2018-02	5
2018-03	36
2018-04	20
2018-05	26
2018-06	17

Tables 3.1 and 3.2 are the samples that show the number of any type of passenger cars sold and EVs sold respectively. As the dates are starting with 2011 and 2018, it indicates the starting year of the data on hand. Because of the fact that, the EV is a newly emerging market, unfortunately there exist not earlier data recorded specially for that type. End date of both datasets are December 2021, which means there are 132 and 48 total rows of instances for the passenger cars and EV respectively.

3.2 Evaluation Metrics

In this study, two main goals are set as estimating the future number of EVs and offering the best EV charging stations places. However, after application and obtaining the results from approaches, determining the goodness rate of these algorithms play a significant role. To determine the goodness level, errors of the outputs should be measured. In the meantime, there exist many ways to measure errors of the mathematical algorithms in the literature. In this chapter, used metrics for the error rates of the proposed models are explained.

Definitions of the used expressions in the Equation (3.1), (3.2), and (3.3) are given below.

F_t: the forecast value at time t

A_t: the actual value at time t

n: total number of observations

t: observation with the specific time stamp

3.2.1 Symmetric Mean Absolute Percentage Error (sMAPE)

In this study, while the EV numbers in the near future is forecasted, to evaluate the goodness of estimation approach, error rates must be determined. With this way, results and the proposed methods can be reliable. One of the used metrics to measure error rate is sMAPE.

sMAPE is a widely used metric to measure the error rate of the forecasted and the actual value. After Armstrong introduced the MAPE (Mean Absolute Percentage Error) in 1985[34], several discussions about biasness of this measure emerged [35]. Therefore, a very similar measure sMAPE is introduced, by Makridakis in 1993, to have more sensible view of error rate [36]. sMAPE shows the accuracy rate based on the percentage error between actual and the forecasted value. This metric is straightforward to apply. The formulation of sMAPE is given in the Equation (3.1) as follows:

$$\text{sMAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|F_t - A_t|}{(A_t + F_t)/2} \tag{3.1}$$

3.2.2 Mean Absolute Error (MAE)

MAE is another statistical error measure, which basically sum of absolute errors divided by sample size of the dataset. Although it is easy to apply, it is a well indicator that directly shows the average gap between actual and forecasted value. Even, in several studies performance advantages of MAE are verified [37], [38]. Basically, the working principle of MAE is the estimated and the actual values are subtracted from each and arithmetic average is taken. Equation (3.2) is the mathematical representation of the metric.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |F_t - A_t| \tag{3.2}$$

3.2.3 Root Mean Square Error (RMSE)

Different metrics are used to measure how well approach is fitted to the used dataset in statistical models. One another example of these metrics that widely and for a long time used is RMSE [39]. This metric simply defined as the measurement of how spread the residuals, which is also called as prediction error, far from fitted regression line. It indicates the density of data around the best-fit line. Even though this metric affected from proportionality of the data (if proportionality is large, RMSE get more and more larger because of the square in its formula), RMSE has the advantage of high sensitivity to outliers [40], [41]. Mathematical formula of the RMSE is shared in the following Equation (3.3).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (F_t - A_t)^2}{n}} \tag{3.3}$$

3.3 Forecasting Models

Forecasting models are tools to make predictions about the future of the related area like sales, demand, currency, supply and so forth. There exist several types of forecasting models such as time series, econometrics, Delphi method etc. [42].
In this study, reason of the forecasting model usage is to predict number of EVs in the upcoming near future in Türkiye. The dataset on hand is number of monthly vehicle sales in Türkiye so, time series forecasting models are used to predict the number of sales. In this subsection, used time series models and their definitions are briefly made.

3.3.1 Autoregressive Distributed Lag (ARDL)

Autoregressive Distributed Lag (ARDL) bound test is a time series analysis approach that was developed by Pesaran et. al. in 2001 which is a kind of method that is used in order to capture long- and short-run causality relationships [43]. ARDL model performs well and seems to be more robust approach for the small sample sized datasets [44]. A basic formula of the ARDL model is given in the Equation (3.4).

$$y_t = \sum_{i=1}^{j} a_i y_{t-i} + \sum_{l=0}^{k} b_l x_{t-l} + e_t \tag{3.4}$$

The dependent variable is regressed on its own lags, independent variables, and independent variables' lags, according to the given Equation (3.4). The number of lags j and k in the aforementioned ARDL model makes it a so called ARDL (j, k) model.

3.3.2 Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) models, that have been introduced by Box and Jenkins in 1970s, are used commonly to better understand a time series data or to predict future points [45], [46]. ARIMA models can be considered as an extension of Autoregressive Moving Average (ARMA) models which is described in 1951 [47]. This method is generally used because of its great ability to explain the data [48]. There are also differentiations of ARIMA like ARIMAX, SARIMA, SARIMAX etc. These so called by products, provide small changes in the parameters to fit models to dataset for better solutions.

An ARIMA model is done by differencing whole coverage of instances. The model for this method generally denoted as ARIMA (p, d, q) where these (p, d, q) parameters are all non-negative and integer. "p" indicates the order of autoregressive model which is number of lags and this parameter determines the AR process (ACF); parameter "d" indicates the number of differencing and "q" is the parameter for order which determines the MA process [49], [50].

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} \epsilon_t + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + .. + \phi_q \epsilon_{t-q} \tag{3.5}$$

Equation (3.5) above is a notation of the general ARIMA model. It can be expressed as the predicted value comes from the linear combination of AR process ($\beta_x Y_{t-x}$), MA process ($\phi_x \epsilon_{t-x}$), and a constant.

3.3.3 Exponential Smoothing (ETS)

Exponential smoothing (ETS) is another widely used method for time series forecasting [51]. It was originally named "exponentially weighted moving average". ETS is a prediction method which uses weighted values of earlier sequence observations to estimate future values. In this method, the highest weight is allocated to the latest observation in an organized fashion as older observations are included [52].

ETS offers smoothing the initial sequence and use it to predict future values of the variable of interest [53]. The process of ETS is useful in which the variables in the series are varying over time. This method is helpful for forecasting series which are showing trend, seasonality or both attributes. Below formulation is the mathematical representation of the ETS model.

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}) \tag{3.6}$$

where F is the forecast value, A is actual observation, α is smoothing constant, t is time-period.

3.3.4 Generalized Linear Models (GLM)

Generalized Linear Models are an extension of linear models. The GLM theory was introduced by John Nelder and his colleagues around 1970s and have been extended by others through time. Arguably, GLMs include the methods that have been used a lot and applied by statisticians [54], [55].

The method could be defined as models where the mean of the response variable is transformable to a linear combination of regressor variables via a link function. A set of GLM whom have the same variance function is called a family of models which generally corresponds to a family of distributions, such as the Gaussian, Poisson or binomial [55].

$$Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i \tag{3.7}$$

Since the GLM model is extension of linear models, it is formulated as in the Equation (3.7). Here, Y_i represents the dependent variable, X_i represents the independent variable, β_0 represents the intercept and β_i represents the coefficient for X_i, and finally, ε_i represents the error for i^{th} observation.

3.3.5 Generalized Least Squares (GLS)

Generalized Least Squares (GLS) is a method that is used for estimating unknown parameters of linear regression models which has residuals that are correlated in between. The GLS estimator has some properties, but the prominent ones are unbiasness, consistency, and efficiency [56]. Main reason of the GLS usage is removing the prediction dependency on differencing variances of observations. With this way, unbiasness is ensured for the forecasted values.

3.3.6 Multivariate Regression

Multivariate regression is, as the name implies, a method to assess the linear relationship where there are more than one predictor and response variables. Aim of the method is to find out how the predictions affected by the varying factors [57]. Even this method helps for better understanding the relationship between variables of the dataset, it sometimes seen as complex and demanding high mathematical calculation level. However, because of the given advantage it is used in many applications. A basic mathematical notation of multivariate regression model is given in the Equation (3.8).

$$Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{3.8}$$

where the dependent variable is Y_i, the independent variable *is* X_i, and the constant is β_0.

3.3.7 Vector Autoregression (VAR)

Vector Autoregressive model is used in forecasting multivariate time series data to check relationships between current and past data indices [58]. This approach generally applied for the real-world problems and seen as a good estimator [59], [60]. Because they can be made conditional on the potential future trajectories of certain model variables, forecasts from VAR models can be highly flexible [60]. Representation of the VAR formula can be written as follows.

$$Y_t = a + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t \tag{3.9}$$

In Equation (3.9), Y is the vector of dependent variable (an nx1 matrix), A is the coefficient matrix (an nxn matrix), a is a vector of intercepts (an nx1 matrix), and ε is error term called as white noise (an nx1 matrix).

3.3.8 Theta

Theta method is a special case of simple exponential smoothing with drift and used because of its simplicity and high accuracy in time series forecasting. Decomposition is essentially the basis of the Theta model, because of that time series can be divided into three parts: residuals, trend components, and seasonal components. The model basically modifies the curves in the dataset with a coefficient called “Theta” as the name implies [61].

3.3.9 Random Forest Regressor (RFR)

Random Forest is an algorithm which could be considered as an extension of decision trees. The method uses many decision trees in order to give accurate predictions and is able to handle a large number of input variables. RFR firstly introduced by Ho in 1995 as “Random Decision Forests” but later it gets the current name [62]. The working principle of the model is constructing decision trees and giving the average values of those as predictions [63]. The RFR model eliminates the overfitting on training set issue observed in decision trees which is one of the most advantages of this model [64].

3.3.10 Random Walk Approaches

The name “Naïve Method” is used interchangeably with the random walk time series model. There exist several random walk approaches used in the literature and applications on related areas such as “Average Value Naïve, Constant Naïve, Seasonal Naïve” and so on. Random walk approach indicates that the dataset follows no distribution and there is not any relationship between the indices of the dataset. Therefore, a noise added to the previous observation as the prediction. The history of this approach dated to 1863 and introduced for the stock market prices [65]. However, Naïve methods are used, and contributions made by many well-known academics through decades [66], [67]. Since the random walk approaches are very simple to apply, it can be interpreted by its formula below.

$$x_t = x_{t-1} + w_t \tag{3.10}$$

In the Equation (3.10) w represents the error term and the prediction made by adding this term to the observed value beforehand.

3.4 Facility Location

The term "facility location" refers to the place(s) chosen by entities at which services are offered in order to maximize efficiency metrics, as well as equity and effectiveness [68]. The optimal placement of facility problem generally studied as operations research branch to find out the best place accordingly to resource limitations and regional factors. Aim of the approaches alter from each other while considering the constraints. The goal can be constructing only one facility, which is known as Weber problem, deployment of minimum number of facilities to satisfy the demand, seeking minimum distance to the sites etc. with several applications like healthcare, waste management and so forth [64], [69]–[71].

Chapter 4

Method Application and Results

This chapter is divided into two sections as forecasting and location selection. In the forecasting section, procedures of data gathering and preprocessing, explanation of forecasting approach and it's results with evaluation metrics are discussed. In the second section, data gathering and preprocessing, mathematical formulation for the best location determination of EV charging stations is handled.

4.1 Forecasting

4.1.1 Data Gathering and Preprocessing

There exists no academic study that gathers EV sales data with a monthly precision and predict future sales amount to optimally find the charging station locations, to the best of knowledge on hand. However, charging stations will be used for many years and expected to satisfy the charging demands, in at least the short and medium terms. For this reason, a study considering only the recent EVs on the road would be inadequate. Hence, it is crucial to consider future EV numbers on the roads to procure a realistic and more applicable approach for deployment of charging stations. Therefore, the EV sales data in a monthly precision is gathered to predict the future sales amount.

There are several sources that used to gather the passenger car sales and EV sales data. Although passenger car sales data is publicly available for Türkiye, needed collaborations are made with several statistical consultancy companies to gather EV sales data.

After all, the overall passenger car data were needed to reorganize, because the shared datasets were comprised of brands' monthly sales. Thus, firstly total sales of the specific month are formed and then, a new dataset, which includes overall sales for each month from January 2011 to December 2021, is created as in the Table 3.1 in the Chapter 3.

Fortunately, EV sales data gathered was an organized and well prepared so, no action is taken to reformat it like for the overall sales.
On the other hand, EV data has very limited observation, since it is a recently emerging technology, another data is required to make prediction properly. This dataset is actually a subtraction of EV sales from overall sales data. What it means by this statement is that a new dataset, which includes just the internal combustion engine cars sales, is created by removing number of EVs from whole number. At the end, there are three datasets, overall sales, internal combustion sales, and EV sales data, available for forecasting.
Date ranges of overall and internal combustion engine cars sales datasets are from January 2011 to December 2021, as stated, and for the EV sales dataset it is from January 2018 to December 2021. As a result, 132 rows of observations for overall and internal combustion engine cars, and 48 rows of EV sales data is prepared to use within the approaches.

4.1.2 Forecasting Approach

In this study, one of the objectives is predicting the future number of EVs on the roads in a few years. To achieve this objective, time series analysis, which is the well-fitting and needed approach, is conducted. Time series analyses are made with the historical data to predict future circumstances. However, the observation amount of the historical data suggested to be preferable more than 100 instances [72]. The primary reason of this number is to properly catch the seasonality and trend, if there exist. Unfortunately, as explained in the Section 4.1, only 48 instances are available in the EV sales dataset. To overcome lack of data problem, different approach is needed to be developed for prediction of future EV sales numbers. For this reason, a novel approach is introduced, which is required to make necessary prediction. In this approach, two different forecast models have been developed, one for overall sales data and the other for the internal combustion engine cars sales data. The logic behind of this approach is that when forecasted number of internal combustion engine cars are removed from the forecasted number of overall car sales the remaining number will be the number of EV in the future. With this way, without using the insufficient EV sales data, which has issue of lack of observation, future number of EVs on the roads is forecasted logically.
Forecasting process is done with two iterations and four runs in total. On account of the fact that, after Covid-19 pandemic hit Türkiye, people avoided buying items excerpt their vital requirements and that decreased the vehicle sales extraordinarily. The first iteration

has been made with the whole data and the forecast results are seemed to be affected dramatically. Therefore, the second iteration is done with the dataset that does not contain the sales in the 2020. Eventually, more logical and foreseen results are obtained.

In addition to all that, TOGG is going to start to mass production in the first quarter of the 2023 and the amount produced until the end of 2023 is 18000 [73]. Thus, a burst of demand will be seen since the authorized people states the sales guarantee. For this reason, the number of TOGG should be added on forecasted EV numbers for achieving better and applicable results in the second step, which is charging station deployment. Addition procedure is parallel to the seasonality of the overall sales. Seasonality coefficient is multiplied monthly with the number of TOGG promised.

Forecasting approaches are trained with the 108 observations and last year's sales data used as the test set. Resulting situations are shared below.

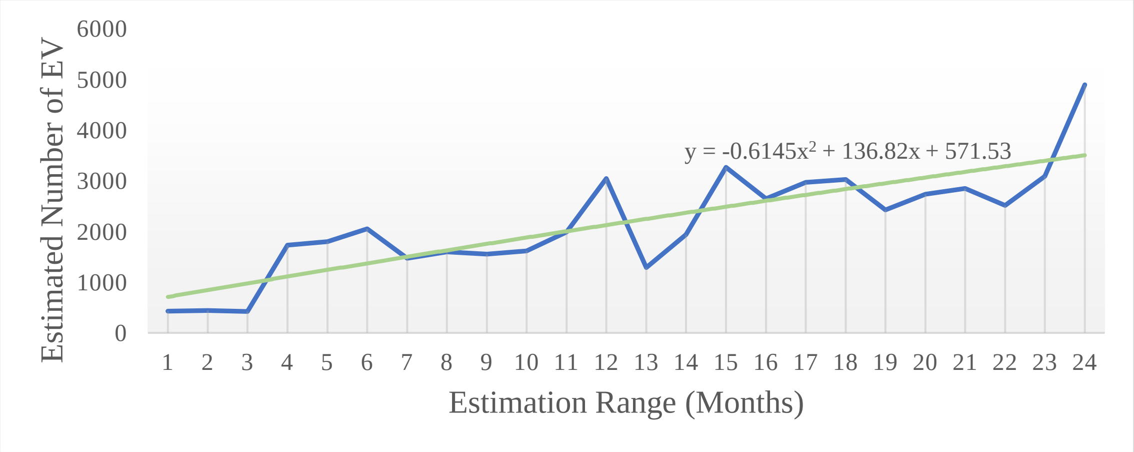

Figure 4.2 Forecast Results for 24 Months

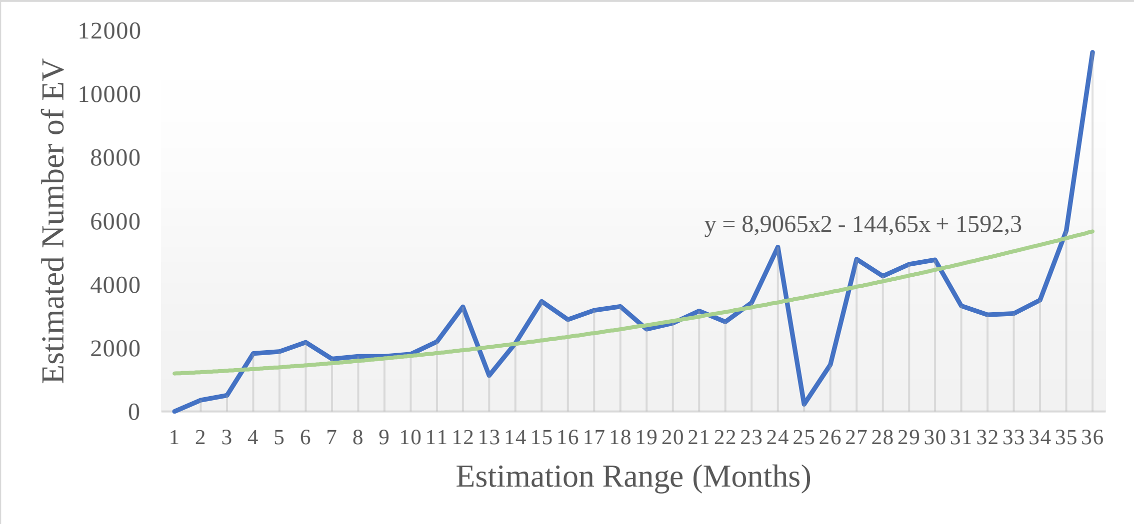

Figure 4.3 Forecast Results for 36 Months

Figures 4.3 and 4.4 illustrates the obtained results for 24 and 36 months. The results given in the tables above are obtained from the estimation approach made with the GLM method. The reason behind choosing the GLM is observing the minimum sMAPE and MAE values, which are given in Table 4.3. Several fluctuations are monitored in the forecasted EV sales results, as it is expected to obtain, because of the nature of vehicle sales in Türkiye. For the past sales, usually an extreme raise in the last two months of years and dramatic decrease in the beginning of the years are seen. Correspondingly, forecasting approach resulted with the similar pattern. As a result, it is expected that there will be approximately 115000 EVs in Türkiye by the end of 2025.

The evaluation metrics are defined and working principal of those explained before. Hereby, the obtained error rates are given in the Table 4.3.

Table 4.3 Error Rates of the Applied Models

Applied Model	sMAPE	MAE	RMSE
Generalized Linear Model	10,4103	8320,3053	11079,5156
Multivariate Regression	11,8479	8408,8946	10345,3683
Theta	11,9579	8451,3415	10487,4450
Generalized Least Square	12,9192	9509,9190	12028,0517
Random Walk (Last Value Naïve)	13,0060	9632,6875	12560,9452
Random Walk (Average Value Naïve)	13,2313	9654,6477	12169,0684
Random Forest Regressor	13,3869	9956,4972	12637,5304
Random Walk (Constant Naïve)	13,3905	9959,4583	12641,1236
Random Walk (Seasonal Naïve)	13,3908	9610,7083	12099,2996
ARIMA (7, 2, 4)	13,3908	9959,7083	12641,4682
Exponential Smoothing	13,3908	9959,7327	12641,5018
Autoregressive Distributed Lag	13,4503	10013,4996	12721,6936

4.2 Location Selection Approach

Main aim of this study is to meet the customers' demand, which is reaching the intercity EV charging services, while minimizing the station placement and charging installation costs. For that purpose, candidate places to be analyzed should be selected. Therefore, the highways under control of the government, which are Ankara – İstanbul, Aydın – İzmir, Mersin – Adana, and Osmaniye – Şanlıurfa, are chosen. Optimization approaches are applied. Data gathering and preprocessing, proposing the approach, and the results are discussed under this section.

4.2.1 Data Gathering and Preprocess

Selected highways include numerous different entrances which divides them into several parts. As this study aims to offer places to deploy charging stations, parts of these highways should be well defined. Parts are formed as road pieces between two consecutive gates.

Table 4.4, 4.5, 4.6, and 4.7 show the following information according to each highway part; the daily average number of passenger cars, daily number of passing average over total number of passenger cars ratio extending to years, averages of the calculated ratios, and the daily expected number of EVs traveling. The daily number of cars traveling between highway parts is directly retrieved from the General Directorate of Highways annual reports [74]–[77]. On the other hand, yearly total passenger cars in Türkiye are used to find out the proportions of the passing cars through highways [78]–[81]. The calculation of the proportions is done by dividing each entry to the total number of passenger cars. Lastly, the number of expected EVs on the highways are computed by using the average ratios and the estimated number of total EVs in Türkiye till the 2025 as in the "Forecasting Approach" section.

Table 4.4 Related Dataset of the Ankara - İstanbul Highway

	2021		2020		2019		2018			
	Total Passenger Car **13710272**		Total Passenger Car **13110657**		Total Passenger Car **12504767**		Total Passenger Car **12393329**			
Highway Parts	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Average Proportion**	**Expected Number of EV**
Doğu İzmit - Sapanca	29118	0.21%	29539	0.23%	33918	0.27%	36295	0.29%	0.25%	288
Sapanca - Adapazari	28482	0.21%	28928	0.22%	33321	0.27%	35314	0.28%	0.24%	282
Adapazari - Akyazi	22771	0.17%	22847	0.17%	27024	0.22%	27046	0.22%	0.19%	223
Akyazi - Hendek	22445	0.16%	21652	0.17%	25617	0.20%	25569	0.21%	0.19%	213
Hendek - Düzce	21638	0.16%	20935	0.16%	24559	0.20%	23256	0.19%	0.18%	202
Düzce - Kaynaşli	19812	0.14%	19117	0.15%	23221	0.19%	21598	0.17%	0.16%	187
Kaynaşli - Abant	19566	0.14%	18562	0.14%	22539	0.18%	20984	0.17%	0.16%	182
Abant - Bolu Bati	20032	0.15%	19203	0.15%	23417	0.19%	21450	0.17%	0.16%	188
Bolu Bati - Bolu Doğu	19335	0.14%	18574	0.14%	22457	0.18%	20518	0.17%	0.16%	181
Bolu Doğu - Yeniçağa	19844	0.14%	19194	0.15%	23166	0.19%	21262	0.17%	0.16%	186
Yeniçağa - Dörtdivan	19847	0.14%	19043	0.15%	22527	0.18%	20987	0.17%	0.16%	184
Dörtdivan - Gerede	19987	0.15%	19084	0.15%	22665	0.18%	20899	0.17%	0.16%	184
Gerede - Çamlidere	15748	0.11%	14233	0.11%	17780	0.14%	15904	0.13%	0.12%	142
Çamlidere - Çeltikçi	16241	0.12%	14806	0.11%	17712	0.14%	16327	0.13%	0.13%	145
Çeltikçi - Akincilar	16807	0.12%	15420	0.12%	18338	0.15%	16872	0.14%	0.13%	150

Table 4.5 Related Dataset of the Aydın - İzmir Highway

Highway Parts	2021 Total Passenger Car **13710272** Daily Average	2021 Ratio to the Total	2020 Total Passenger Car **13110657** Daily Average	2020 Ratio to the Total	2019 Total Passenger Car **12504767** Daily Average	2019 Ratio to the Total	2018 Total Passenger Car **12393329** Daily Average	2018 Ratio to the Total	Average Proportion	Expected Number of EV
Işikkent - Tahtaliçay	35670	0.26%	30451	0.23%	32322	0.26%	32711	0.26%	0.25%	292
Tahtaliçay - Torbali	32789	0.24%	28122	0.21%	30578	0.24%	30092	0.24%	0.24%	271
Torbali - Belevi	24839	0.18%	20553	0.16%	23678	0.19%	23831	0.19%	0.18%	207
Belevi - Germencik	20296	0.15%	18965	0.14%	19657	0.16%	19461	0.16%	0.15%	174
Germencik - Şevketiye	18005	0.13%	16213	0.12%	17667	0.14%	16997	0.14%	0.13%	153

Table 4.6 Related Dataset of the Mersin - Adana Highway

	2021		2020		2019		2018			
	Total Passenger Car **13710272**		Total Passenger Car **13110657**		Total Passenger Car **12504767**		Total Passenger Car **12393329**			
Highway Parts	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Average Proportion**	**Expected Number of EV**
Serbest Bölge-Tarsus	21634	0.16%	19358	0.15%	22068	0.18%	18295	0.15%	0.16%	181
Tarsus-Çamtepe	20275	0.15%	18266	0.14%	20758	0.17%	17100	0.14%	0.15%	170
Çamtepe-Yenice	21343	0.16%	19300	0.15%	21937	0.18%	18108	0.15%	0.16%	180
Yenice-Adana Bati	27158	0.20%	25467	0.19%	28475	0.23%	23375	0.19%	0.20%	232
Adana Doğu-Ceyhan	20083	0.15%	16572	0.13%	18436	0.15%	17216	0.14%	0.14%	161
Ceyhan-İskenderun Ayr. Bati	19389	0.14%	16222	0.12%	18058	0.14%	16887	0.14%	0.14%	157

Table 4.7 Related Dataset of the Osmaniye – Şanlıurfa Highway

	2021		2020		2019		2018			
	Total Passenger Car **13710272**		Total Passenger Car **13110657**		Total Passenger Car **12504767**		Total Passenger Car **12393329**			
Highway Parts	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Daily Average**	**Ratio to the Total**	**Average Proportion**	**Expected Number of EV**
Toprakkale-Osmaniye	14323	0.10%	11664	0.09%	12502	0.10%	11776	0.10%	0.10%	112
Osmaniye-Düziçi	15370	0.11%	12696	0.10%	13628	0.11%	12769	0.10%	0.11%	121
Düziçi-Bahçe	15003	0.11%	12373	0.09%	13309	0.11%	12421	0.10%	0.10%	118
Bahçe-Nurdaği	14035	0.10%	11505	0.09%	12363	0.10%	11543	0.09%	0.10%	110
Nurdaği-Narli	12054	0.09%	9699	0.07%	10427	0.08%	9654	0.08%	0.08%	93
Narli-Gaziantep Bat	11386	0.08%	9034	0.07%	9780	0.08%	8990	0.07%	0.08%	87
Gaziantep Bati-Gaziantep Kuzey	8126	0.06%	6351	0.05%	6466	0.05%	6094	0.05%	0.05%	60
Gaziantep Kuzey-Gaziantep Doğu	8075	0.06%	6097	0.05%	5998	0.05%	5570	0.04%	0.05%	57
Gaziantep Doğu-Nizip	10348	0.08%	8941	0.07%	10009	0.08%	8860	0.07%	0.07%	85
Nizip-Birecik	8436	0.06%	6442	0.05%	7030	0.06%	6243	0.05%	0.05%	62
Birecik-Suruç	7903	0.06%	6046	0.05%	6492	0.05%	5899	0.05%	0.05%	58
Suruç-Şanliurfa	7554	0.06%	5736	0.04%	6185	0.05%	5662	0.05%	0.05%	56

As indicated above tables, there exist 15, 5, 6, and 12 parts on the Ankara – İstanbul, Aydın – İzmir, Mersin – Adana, and Osmaniye – Şanlıurfa Highways respectively. Implication of these numbers are that the candidate charging station places are in between these parts. For better understanding, following example can be given:

- Last row of the Table 4.7 is the last part of the Osmaniye – Şanlıurfa Highway is "Suruç – Şanlıurfa",
- The daily average number of the passenger cars on this part is 7554 in 2021 and the total number of passenger cars in Türkiye is 13710272 in 2021,
- The daily average over the total number of passenger cars is 0.06 percent,
- The same procedure applies for the 2020, 2019, and 2018,
- The average proportion is the arithmetic mean of the ratios of the years on the same rows,
- The expected number of EV is the output of the multiplication of the average proportion and the forecasted number of EVs as stated in the Section 4.2 in this study.

Studies on the field of transportation are usually done by considering the rush hours. Therefore, charging station location problem should be solved based on the rush hours. To calculate the density while the rush hour, daily expected number of EVs, as in the Tables 4.4, 4.5, 4.6, and 4.7, are divided into 24 to find out the hourly EV pass numbers. Then the output is multiplied by two, which can be general assumption according to TOMTOM, for the rush hour density [82]. In addition to those, people who own an EV are generally willing to recharge their vehicle when the SoC (State of Charge) is below 30% [83]. Because of this reason, SoC of EVs on the highway parts are divided evenly into four classes as less than 30%, between 30 and 45%, between 45 and 60%, and more than 60%. The resulting numbers for the less than 30% SoC present the number of EVs require charging on the given highway parts which is demonstrated in the Table 4.8 below. Parts are numbered accordingly to Table 4.4, 4.5, 4.6, and 4.7.

Table 4.8 Expected Demand of Every Highways on Each Parts

Ankara – İstanbul		Aydın – İzmir		Mersin – Adana		Osmaniye – Şanlıurfa	
Highway Parts	**Charging Demand**	**Highway Parts**	**Charging Demand**	**Highway Parts**	**Charging Demand**	**Highway Parts**	**Charging Demand**
1	6	**1**	6	**1**	4	**1**	2
2	6	**2**	6	**2**	4	**2**	3
3	5	**3**	4	**3**	4	**3**	2
4	4	**4**	4	**4**	5	**4**	2
5	4	**5**	3	**5**	3	**5**	2
6	4			**6**	3	**6**	2
7	4					**7**	1
8	4					**8**	1
9	4					**9**	2
10	4					**10**	1
11	4					**11**	1
12	4					**12**	1
13	3						
14	3						
15	3						

Other must have information for the study is ranges of the existing EVs. Without consideration of the ranges, mathematical model and its outcomes will only be irrelevant and useless.

Brands have different strategies for the battery of an EV. Some seek for the long-distance coverage, however, several of them aim to offer lighter vehicle. Even the same brand can have different market plan for its models. Therefore, different brands and models should have been considered. In the Table below, its seen that the ranges alter within each brand and models. Ranges have a non-negligible effect on the results, they change the constraints status which also directly affects the satisfaction level of the customers.

Table 4.9 Range Information of Several Brands and Models [11]

BRAND & MODEL	RANGE (KM)
LUCID AIR DREAM EDITION R	685
Mercedes EQS 450+	640
Tesla Model S Dual Motor	570
BMW I7 XDrive60	510
Audi Q8 E-Tron 55 Quattro	495
Polestar 3 Long Range Dual Motor	490
Volkswagen Id.3 Pro	350
Toyota Bz4x AWD	330
Opel Corsa-E	285
Mini Cooper Se	180
Mazda Mx-30	170
Renault Twingo Electric	130
Smart Eq Fortwo Cabrio	95

4.2.2 Mathematical Modelling

In this section, mathematical model to solve the current problem is given. Following content is basically explanation of the data, assumptions made before running the mathematical model, notations and their definition, and lastly the formulation part.

4.2.2.1 Assumptions of the Mathematical Model

A model is a representation of the real world to have better understanding on the actual situations [84]. Therefore, to solve a real-world problem, it is needed to be made some key assumptions. In this study, to make the problem able to be solved several assumptions have been made. Those assumptions are as followings:

- The drivers do not have extraordinary driving style,
- Driving ranges of the EVs are constant and invariable,
- The average range of the included EV models is applicable for every customer,
- Neither electric-truck nor electric-motorcycle is existing in the system,
- Electricity in the charging system is not finite and not interruptible,
- No queue forms in front of the charging stations.

4.2.2.2 Modelling

Sets/Indices

i parts of the Highways i = {1, 2, 3, …, n},

Data/Parameters

S: cost of construction of a new charging station ($),

C: cost of a charger installation on a station ($),

P: penalty cost of an unsatisfied charging demand ($),

I: maximum number of stations can be placed,

T: maximum number of chargers can be installed on a station,

M: a big number,

D_i*: charging demand on the highway part i,*

Decision Variables

X_i = *{1, if the highway part i is selected to locate EV charging station; 0, otherwise},*

CH_i = *number of chargers installed on the highway part i,*

UD_i = *number of unsatisfied charging demand on the highway part i,*

ND_i = *number of the updated demand on the highway part i,*

4.2.2.3 Formulation

Objective Function

$$z^* = min\, z = \sum_{i}^{n} (S \cdot X_i + C \cdot CH_i + P \cdot UD_i) \quad \textbf{(4.1)}$$

Objective function (4.1) is to minimize the total cost, which consist of construction of a charging station, installing chargers on the given station, and the penalty cost of unsatisfied charging demand on the given highway. Ordinarily, the most desired outcome is to have maximum customer satisfaction with the minimum cost, which is the first necessity of the study.

Constraints

$$M \cdot X_i \geqslant CH_i \qquad \forall i \qquad \textbf{(4.2)}$$

$$\mathrm{CH}_i \geqslant X_i \qquad \forall i \qquad \textbf{(4.3)}$$

Constraint (4.2) defined for that the chargers are not located if there exist no station on the highway part *i*. The reason of this constraint is any charger cannot be established onto not selected station intuitively. Constraint (4.3) prevents the model to not select any place as charging station which does not have any charger capacity. Constraint (4.3) also ensures decision variable X_i to take value of 1, if the chargers are located at there. On the other hand, it archives and lists the chosen locations.

$$D_i - CH_i = UD_i \qquad \forall i \qquad \textbf{(4.4)}$$

$$ND_i = D_i + UD_{i-1} \qquad \forall i\ (i \neq 1) \qquad \textbf{(4.5)}$$

$$ND_i - CH_i = UD_i \qquad \forall i \qquad \textbf{(4.6)}$$

Constraints (4.4), (4.5), and (4.6) are about the demand limitations and updating processes. Constraint (4.4) and (4.6) defines unsatisfied charging demand also, values that these constraints give as outputs are keep the results like database. Constraint (4.5) updates the demand where the whole demand on the last highway part is not met.

$$\sum_{i}^{n} X_i \leqslant I \qquad \textbf{(4.7)}$$

$$X_i - X_{i-1} \leqslant 1 \qquad \forall i\ (i \neq 1) \qquad \textbf{(4.8)}$$

$$CH_i \leqslant T \qquad \forall i \qquad \textbf{(4.9)}$$

Constraints (4.7), (4.8), and (4.9) are prevention constraints that (4.7) ensures model to not locate more than number of candidate locations, constraint (4.8) states that the two consecutive parts cannot have a station at the same time, and constraint (4.9) limits model to not install chargers more than desired. The existence of the constraint (4.9) ensures that the electric limit of the infrastructure is not compelled.

$$X_i \in \{0,1\} \qquad \forall i \qquad \textbf{(4.10)}$$

$$CH_i, UD_i, ND_i \in \mathbb{N} \qquad \forall i \qquad \textbf{(4.11)}$$

Constraints (4.10) and (4.11) are to define variables. These constraints ensure that X_i is a binary constraint, and CH_i, UD_i, and ND_i can take values as natural numbers.

4.2.3 Results

Given formulation in the sub-section 4.3.2 is examined by using Python software as optimization tool. Formulation and constraints are coded properly to the platform and runs are taken and all results are obtained as optimal.

There exists total four runs for the whole process because of the fact that, the number of highway applicable is four. Obtained results are shared with the following table 4.10, 4.11, 4.12, and 4.13. Tables consist of the highway names, parts indicators, and the decision variables outputs of the model.

Table 4.10 Results of Variables of Ankara - İstanbul Highway

Ankara - İstanbul Highway

Parts	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
X_i	0	1	0	1	0	1	0	1	0	1	0	0	0	0	0
CH_i	0	6	0	7	0	8	0	8	0	8	0	0	0	0	0
UD_i	3	0	3	0	4	0	4	0	4	0	4	8	13	19	25
ND_i	-	6	3	7	4	8	4	8	4	8	4	8	13	19	25

Throughout the 15 parts of Ankara – İstanbul Highway, resulting station placement offer seen as five, while the total chargers on those stations are 37. With the construction cost, charger installation cost and unsatisfied charging demands' penalty total cost turned out to be 914550 USD.

Table 4.11 Results of Variables of Aydın - İzmir Highway

Aydın - İzmir Highway

Parts	**1**	**2**	**3**	**4**	**5**
X_i	1	0	1	0	0
CH_i	6	0	8	0	0
UD_i	0	6	2	6	9
ND_i	-	6	10	6	9

The least number of parts holder highway, which is Aydın – İzmir, is offered to construct just two stations. Along with two stations, 14 chargers offered to be installed and the end cost result in 401900 USD.

Table 4.12 Results of Variables of Mersin - Adana Highway

Mersin - Adana Highway

Parts	**1**	**2**	**3**	**4**	**5**	**6**
X_i	0	1	0	1	0	0
CH_i	0	8	0	8	0	0
UD_i	4	0	4	1	4	7
ND_i	-	8	4	9	4	7

The third analyzed highway is Mersin – Adana Highway and total cost of station construction, charger installation, and the penalty costs of unsatisfied demands end up as 392000 USD. In this highway, mathematical model suggested to construct two stations with eight chargers installed each.

Table 4.13 Results of Variables of Osmaniye - Şanlıurfa Highway

Osmaniye - Şanlıurfa Highway

Parts	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
X_i	0	0	1	0	0	1	0	0	1	0	0	0
CH_i	0	0	7	0	0	6	0	0	4	0	0	0
UD_i	2	5	0	2	4	0	1	2	0	1	2	3
ND_i	-	5	7	2	4	6	1	2	4	1	2	3

Even though the Osmaniye – Şanlıurfa Highway has many parts, low demand occurs, because of the number of vehicles using this highway is not much, and this leads model to offer few stations to satisfy the charging demand. As in the Table 4.12, number of stations to be constructed is three and the charger on them 7, 6, and 4 respectively. As a result, overall cost turned out as 487600 USD.

Chapter 5

Conclusion and Future Prospects

5.1 Conclusions

Electric vehicles are one of the increasingly widespread and environmentally friendly transportation methods. However, one of the most important requirements for the widespread use of electric vehicles is to provide a vehicle charging network. Most of the studies on this subject focus on popular destinations within the city. Although various urban areas are frequently used in daily life, due to the number of possible charging stations e.g. commuter parking lots, shopping mall park areas etc., they can generally offer a sufficient solution to the daily charging need. However, for intercity journeys, finding adequate charging stations, especially on highways, is of great importance in order to complete the journey. In this study, a decision model has been proposed to determine the location of electric vehicle charging stations on highways. In order to obtain a realistic approach to the placement of charging stations, the number of electric vehicles that will hit the roads in Türkiye in the next few years is estimated and this number is used as an important input in the facility positioning model. Then, an optimization model was created to determine the optimum locations for the charging stations and number of chargers on highways. The proposed model covers all the state highways in Türkiye and determines the optimum charging stations' locations and the expected number of chargers that will be needed by the charging service providers, which will ensure that passengers traveling with their electric vehicles do not experience charging problems.

5.2 Societal Impact and Contribution to Global Sustainability

EVs have the potential to make a significant impact on sustainability. They emit zero emissions at the time of usage, which reduces air pollution and fights climate change. In addition, the widespread adoption of EVs can lead to the development of a more sustainable transportation system. The need for charging infrastructure and the integration of renewable energy sources into the grid can drive innovation and investment in these areas. This can lead to improvements in energy efficiency, the expansion of clean energy sources, and a reduction in greenhouse gas emissions.

As a new adopter of this emerging technology, it is crucial for Türkiye to design EV-connected systems and infrastructures that are prepared for the future. By installing these systems, it not only will increase the adoption of EVs, but also it will raise awareness among people about the benefits of EVs, directly contributing to the improvement of air quality, reduction of energy consumption, and decrease in noise pollution, among other things.

Furthermore, by considering the SDGs, the country can ensure that the development and implementation of EV-related policies and infrastructure align with the goal of creating a more sustainable future. This can include targeting the deployment of charging stations in underprivileged areas, increasing accessibility to EVs for low-income households, and supporting the development of locally produced EVs and charging infrastructure.

Overall, the widespread adoption of EVs can lead to significant improvements in sustainability, but it is important to ensure that these developments are inclusive and equitable. By considering the SDGs, Türkiye can ensure that the transition to EVs benefits all members of society and contributes to the creation of a more sustainable future.

5.3 Future Prospects

In this study, various approaches are presented for EV charging station locations and the number of chargers required for vehicles expected to need charging on state-controlled highways. In this process, analyzes were made on the daily average number of vehicles presented in the highway parts. In order to advance these studies, it is planned to develop the presented study with the time stamp data of number of vehicles entering and exiting the highways. With this approach, it is considered that more real-life results will be obtained, since information about short-distance journeys on highways will also be obtained.

On the other hand, it is thought that it would be beneficial to include the lengths of the highway segments and thus to add different scenarios about the SoC situations of EVs to the study. Thanks to these scenarios to be created, it is foreseen that different alternatives will be created for charging service providers and steps will be taken to increase the satisfaction of EV users.

Another variant can be applying the simulation-based approaches by analyzing the highway density. With this way, probabilistic situations can be observed better and bottlenecks and stochasticity could be considered while offering the best sites for the EV charging stations.

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J1) M. Sütçü, KN. Şahin, Y. Koloğlu, ME. Çelikel, İT. Gülbahar, Electricity Load Forecasting Using Deep Learning and Novel Hybrid Models (Feb. 2022).

J2) M. Sütçü, İT. Gülbahar, Optimal location determination of electric vehicle charging stations: A case study on Turkey's most preferred highway (Jun. 2022).

C1) M. Sütçü and İ. T. Gülbahar, A Study on the Effect of Electric Vehicle Charging Stations on Carbon Emissions (May. 2022).

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C4) S. Gören, İ. Gülbahar, M. Pinar, Statistical approach for table tennis athletes' success (Jul. 2018).