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Optimizing Electric Vehicle Charging Station Location on Highways: A Decision Model for Meeting Intercity Travel Demand

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Abstract: Electric vehicles have emerged as one of the top environmentally friendly alternatives to traditional internal combustion engine vehicles. The development of a comprehensive charging infrastructure, particularly determining the optimal locations for charging stations, is essential for the widespread adoption of electric vehicles. Most research on this subject focuses on popular areas such as city centers, shopping centers, and airports. With numerous charging stations available, these locations typically satisfy daily charging needs in routine life. However, the availability of charging stations for intercity travel, particularly on highways, remains insufficient. In this study, a decision model has been proposed to determine the optimal placement of electric vehicle charging stations along highways. To ensure a practical approach to the location of charging stations, the projected number of electric vehicles in Türkiye over the next few years is estimated by using a novel approach and the outcomes are used as crucial input in the facility location model. An optimization technique is employed to identify the ideal locations for charging stations on national highways to meet customer demand. The proposed model selects the most appropriate locations for charging stations and the required number of chargers to be installed, ensuring that electric vehicle drivers on highways do not encounter charging problems.

Keywords: urban studies; electric vehicle; charging station; time series analysis; facility location

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1. Introduction

The use of a wide range of tools by people over the years has simplified everyday life considerably. Humans have employed various modes of transportation, such as walking, domestic horses, and bicycles, for purposes such as finding food, conducting business, and meeting others, for centuries. However, the popularity of faster means of transportation has increased exponentially over the past two centuries. Internal combustion engine vehicles, which have been in use since the 19th century, have seen continuous advancements, with exponential acceleration in their usage. However, air pollution and global warming have raised questions about the place of fossil fuel-dependent vehicles in our lives [1,2]. Senna and Radwan (2014) suggested an ideal method for creating a precise microscopic transportation emissions model [3]. This model aims to achieve sufficient accuracy as a substitute for predicting carbon dioxide (CO_2) emissions on limited-access highways, offering an alternative to the traditional approach of using a traffic model and integrating the outcomes into an emissions model. Also, Nocera and Cavallaro (2014) introduced a two-stage process (balancing and valuation) for explicitly incorporating CO_2 into mobility plans [4]. Cavallaro and Nocera (2022) introduced an approach to assess the efficiency of photovoltaic noise barriers on motorway A22 in Italy [5]. They conducted a cost-benefit analysis, considering existing policies and comparing the results with a specified benchmark scenario. Several researchers provided an extensive research synthesis on externalities related to energy and mobility [6]. In this analysis, they consolidated information from 139 studies to investigate the undisclosed expenses associated with energy. According to the World Bank, the transportation sector contributed to more than 20% of CO_2 emissions worldwide in 2014 [7]. These adversities have led to opportunities such as the growing trend of using alternative energy vehicles [8]. Figure 1 illustrates the increase in the number of these vehicles sold. This trend not only has led to increased sales of such vehicles but has also accelerated the development of requisite infrastructure and by-products. Electric vehicles (EVs) are a more viable option for sustainable energy usage in the transportation industry, particularly those energized with alternative fuels [9]. Therefore, studies on the infrastructure required for EVs have become one of the main topics of conversation.

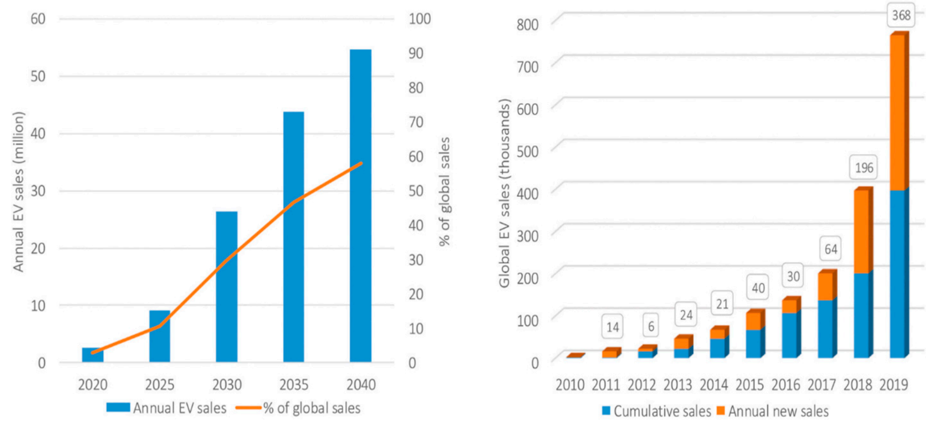

Figure 1. EV sales forecast and global EV sales (Gönül et.al. 2021, [10].)

Qian et al. proposed a multi-agent deep reinforcement learning (MA-DRL) approach to simulate the pricing dynamics in an urban transportation network [11]. This method aims to establish the best charging prices for an individual electric vehicle charging station. Zhang et al. proposed an imitative multi-agent spatio-temporal reinforcement learning (RlCharge) framework designed to intelligently suggest publicly accessible charging stations [12]. This approach considers a combination of different long-term spatio-temporal factors for more informed recommendations. Moreover, Zhang et.al. (2022) approached the charging station pricing problem by framing it as a mixed competitive–cooperative multi-agent reinforcement learning task [13]. Each charging station is treated as an agent, and they introduce a shared meta generator to create tailored dynamic pricing policies for a wide range of agents based on extracted meta characteristics. In addition, different studies have been conducted in the literature for different countries and cities to select charging station locations for EVs [14–18].

An effective charging station infrastructure is imperative for providing maintenance and support services to electric vehicles. However, it should be noted that infrastructure development is still in its emerging stage and priority areas and requirements must be identified to enable effective management of limited resources to meet the needs of EV customers. One of the biggest limitations faced by EV users is the lack of adequate charging stations, which hinders the popularity of alternative fuel vehicles [19–21]. Analyzing various aspects of charging station identification and location is crucial for developing an effective plan. Several cases have been analyzed and various methods have emerged, which are discussed further.

The rapid pace of technological development in various fields has necessitated the development of relevant infrastructures to meet people's daily needs. The use of electric vehicles has increased significantly, and the installation of charging stations is a crucial factor in the widespread adoption of these vehicles. Although electric vehicles are becoming more preferred for inner-city use due to short-distance trips and easy access to charging, intercity transportation requires charging stations to be placed along highways to spread the use of electric vehicles. Ensuring user satisfaction by allowing them to charge their EVs when necessary is essential in this process, as leaving a vehicle stranded on the highway can cause safety concerns and additional costs. On the other hand, charging service providers face several costs in establishing charging stations, such as placement costs, infrastructure costs, and equipment costs. When optimizing the locations of charging stations while considering the number of EVs, several steps must be taken, such as estimating the number of future EVs and determining the location of charging stations on highways. This study aims to address these problems and provide solutions. The findings and results of the proposed solutions will be presented in more detail.

Various methods used to forecast future situations are examined. The autoregressive distributed lag (ARDL) model was used to study the relationship between stock market development and economic growth in Pakistan, finding a bidirectional long-term relationship and a one-way short-term causality from stock market development to economic growth [22]. Another study used the ARDL model to examine the long-run demand for money in Hong Kong, identifying a long-run relationship between various economic factors [23]. The autoregressive integrated moving average (ARIMA) model was employed to analyze household electric consumption patterns using daily, weekly, monthly, and quarterly time series data, with different ARIMA models selected based on root mean square error (RMSE) values [24]. An ARIMA model was compared with LSTM for predicting average stock prices using NASDAQ data and was found to perform better than LSTM except for daily price predictions [25]. Exponential smoothing (ETS) was utilized for forecasting COVID-19 parameters across various countries and outperformed other methods such as LSTM when assessed using RMSE, MAE, and MSE metrics [26]. Several studies were conducted by using the generalized linear model (GLM) and its extensions. The approaches mentioned were used in a study focusing on air pollution and the relative risk of cardiopulmonary hospital admissions, where the GLM with natural cubic spline performed better than generalized linear mixed models (GLMMs) with natural cubic spline [27]. In another example, the GLM was used to investigate the impact of meteorological factors on the spread of COVID-19 in Africa and revealed that the relationship between virus spread and meteorological factors varies between countries [28]. Multivariate regression is one of the most popular prediction methods. A study proposed as an alternative to analytical approaches to determine the pressure of the bottom of the well in mechanized oil-producing wells proved to be more functional despite some limitations [29]. Researchers used a multivariate regression model to study the impact of energy consumption and economic growth on CO_2 emissions in some Middle Eastern and North African countries [30].

The second and main part of this study focuses on the optimal locations of electric vehicle charging stations. The following literature review highlights various approaches to improving the service satisfaction of electric vehicle (EV) drivers by optimizing charging station locations. Qin and Zhang suggested that regulating the schedules and locations of charging stations can increase satisfaction [31]. They analyzed waiting times and proposed revisions to the locations of charging stations. A case study was conducted South Korea using actual traffic flow data from the Korean Expressway network. They compared three different methods—multi-rotation, forward myopic, and backward myopic optimization—and found that the multi-rotation optimization model was the most suitable for large-scale network problems [21]. Another study aimed to reduce the time lost by EV drivers when reaching charging stations by considering traffic density and charging station capacity [32]. The researchers use a genetic algorithm to divide the region into nine sub-regions and successfully proposed a solution to satisfy EV customers. A research group presented a geographic information system (GIS)-based multi-criteria decision analysis approach for selecting charging station locations [33]. They used the fuzzy analytical hierarchy process (AHP) for criteria prioritization and the technique for order preference by similarity to ideal solution (TOPSIS) for ranking potential sites. The study was applied to the interior city of Ankara, and as a result, alternative site locations were suggested.

The main problem of this study is not merely theoretical but also a matter of global concern, as already discussed. Companies engaged in related industries, non-governmental organizations, and even country leaders have weighed in on this widespread issue. Also, in late 2021, the United Nations Climate Change Conference (COP26) was held in Scotland from 31 October to 12 November, focusing on climate change and global warming. A declaration to manufacture zero-emissions cars and vans by 2035 was signed by 33 countries—including Türkiye—40 cities, 11 automotive manufacturers, and 27 fleet owners [34].

Another motivation for this study is the investment in EV technology and manufacturing by TOGG (Türkiye's Automobile Joint Venture Group) in Türkiye, with the manufacturing process set to commence in 2022 [35]. Therefore, the region would observe a surge in the demand for charging stations. However, there are not many studies on this topic, particularly those that identify optimal charging station locations in Türkiye, especially on highways. This study offers a proposal for optimum charging station locations on highways that can meet the demand of future customers.

Electric vehicle usage in Türkiye is rising exponentially, especially considering TOGG's investment and Türkiye's commitment to phasing out the manufacturing of diesel and gasoline vehicles by 2035. This study's central motivation is to develop a suitable, environmentally friendly model for efficient electric vehicle infrastructure based on Türkiye's future progress in electric cars. To efficiently determine the optimal quantity and location of charging stations for the best level of customer satisfaction, one must consider estimating the number of EVs that will exist in the associated regions. However, no studies have been conducted in this field to predict the future number of EVs in Türkiye, making it relevant to estimate the number of EVs that will hit the road in the coming years analytically, as this study aims to do. The number of EVs predicted would provide brief information on the demand level of future customers and a basis for determining the best locations for charging stations.

Analyzing the number and locations of charging stations means specifying the application area. Although people can usually find adequate daily charging solutions due to numerous alternative charging stations in urban areas, those traveling between cities far apart must consider the distances involved. Electric vehicle battery technology has an average range of 340 km currently [36]. For a trip of about 450 km, such as from İstanbul to Ankara, vehicles may need two full charges. Hence, when establishing charging stations, the range covered by an EV should be considered.

All in all, the use of electric vehicles is on the rise globally, driven by concerns about air pollution, climate change, and the need for sustainable transportation solutions. In Türkiye, the commitment to abandoning traditional vehicles by 2035, along with significant investments in EV technology, underscores the importance of developing efficient and environmentally friendly charging infrastructure. This study is motivated by the urgent need to address the challenges associated with the increasing demand for EVs and the necessity of a charging network. By strategically determining the optimal locations and quantities of charging stations, the aim is to ease range anxiety, enhance customer satisfaction, and contribute to the widespread adoption of EVs in Türkiye. Therefore, the research question of this study can be framed as follows: In light of variables including future EV adoption, intercity travel patterns, and environmental sustainability, how can the best sites and number of electric car charging stations be strategically established in Türkiye to accommodate the growing demand for electric vehicles?

The establishment of electric vehicle (EV) charging stations, while contributing to the adoption of sustainable transportation, can potentially have several environmental effects. It is crucial to carefully assess and address these impacts to ensure the overall sustainability of EV charging infrastructure. Some potential environmental effects include energy source dependency, land use and habitat disruption, resource extraction for infrastructure development, visual and noise pollution, grid reliability challenges, and life cycle emissions. To address these potential environmental effects, it is essential to adopt a holistic approach, incorporating renewable energy sources, sustainable construction practices, and comprehensive life cycle assessments into the planning, implementation, and operation of electric vehicle charging infrastructure.

The chosen locations for electric vehicle (EV) charging stations can have significant economic impacts, influencing various sectors and aspects of the economy. Potential economic impacts associated with the selected locations for EV charging stations include local business development, tourism and hospitality, real estate value, job creation, technology and innovation, utility revenue and grid enhancements, government revenue, and environmental savings. Careful consideration of these economic impacts when selecting charging station locations is crucial for maximizing the positive outcomes and ensuring a well-rounded, sustainable integration of EV infrastructure into the broader economy.

The installation of electric vehicle (EV) charging stations introduces various safety and security implications that need to be carefully considered and addressed. The potential safety and security concerns related to the deployment of EV charging infrastructure include electrical safety, vehicle and pedestrian safety, cybersecurity risks, vandalism and theft, user authentication and payment security, and natural disasters and climate events. Addressing these safety and security considerations requires a multi-faceted approach involving collaboration between stakeholders, adherence to industry standards, ongoing risk assessments, and the implementation of robust safety protocols. As EV charging infrastructure continues to expand, staying vigilant and proactive in managing these concerns is crucial to ensuring the overall safety and security of the system.

In conclusion, although related studies have explored numerous approaches to optimizing charging station locations globally, there is a noticeable gap in the literature about Türkiye’s specific needs and circumstances. The demands raised for EVs, particularly with Türkiye’s commitment to zero-emission vehicles, requires a tailored approach that considers the unique geography, intercity travel patterns, and anticipated growth of EVs in the region. Additionally, the lack of studies predicting the future number of EVs in Türkiye poses a significant gap in understanding the potential demand for charging stations. This study aims to fill this void by providing a comprehensive analysis that addresses the specific challenges and opportunities associated with developing an optimal EV charging infrastructure in Türkiye, particularly on highways, where intercity travel demands efficient charging solutions.

The remainder of this article is as follows. In section two, the forecasting approaches used to estimate the number of EVs in the Türkiye are shared, along with the results. The third section includes the mathematical model built to determine the optimal EV charging station locations and the number of chargers in them, as well as the results received from these models. In the last part, the fourth and the fifth sections, a conclusion is made and the future prospects of this study are discussed, respectively.

2. Forecasting

2.1. Data Gathering and Preprocessing

In the literature, to the best of our knowledge, there are no studies that collect EV sales data with monthly precision and forecast future sales to find optimal charging station locations. However, charging stations will be used for many years and are 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 the future number of EVs on the road to procure a realistic and more applicable approach for the deployment of charging stations. Therefore, monthly EV sales data were gathered to predict the number of future sales.

Several sources were used to gather passenger car sales and EV sales data. Although passenger car sales data are publicly available for Türkiye, collaborations were carried out with several statistical consultancy companies to gather EV sales data.

The overall passenger car data ended up needing to be reorganized because the shared datasets were comprised of brands' monthly sales. Thus, the total sales from a specific month were determined first and then a new dataset that included overall sales for each month from January 2011 to December 2021, was created. Fortunately, the EV sales data that were collected were well organized and prepared, so no action was taken to reformat them as with those of overall sales.

On the other hand, there has been very limited observation of EV data; since it is a recently emerging technology, more data are required to make proper predictions. This dataset is actually a subtraction of EV sales from the overall sales data. This means that a new dataset, which includes just the internal combustion engine cars sales, was created by removing the number of EVs from the total number. In the end, there were three datasets—overall sales, internal combustion sales, and EV sales data—available for forecasting.

The date ranges of the overall and internal combustion engine car sales datasets were from January 2011 to December 2021, as stated, and for the EV sales dataset the range was 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 were prepared to use with the approaches.

2.2. Forecasting Approach

In this study, one of the objectives was to predict the future number of EVs on the road in a few years. To achieve this objective, time series analysis, which was the best fitting and necessary approach, was conducted. Time series analyses are conducted with historical data to predict future circumstances. However, 100 instances of historical data observations have been suggested to be ideal [37]. The primary reason behind this number is that it allows for properly catching the seasonality and trends, if they exist. Unfortunately, as explained in Section 2.1, only 48 instances were available in the EV sales dataset. To overcome this problem of the lack of data, a different approach needed to be developed for the prediction of future EV sales numbers. For this reason, a novel approach was introduced to make the necessary prediction. In this approach, two different forecast models were developed: one for the overall sales data and the other for the internal combustion engine car sales data. The logic behind 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 is the future number of EVs. With this method, without using the insufficient EV sales data, which had the issue of a lack of observation iterations, the future number of EVs on the roads was forecasted logically.

The forecasting process was carried out with two iterations and four runs in total. After the COVID-19 pandemic hit Türkiye, people avoided buying items except for vital requirements, which decreased vehicle sales extraordinarily. The first iteration was carried out with the entire dataset, and the forecast results seemed to be affected dramatically. Therefore, the second iteration was completed with the dataset that did not contain the sales in 2020. Eventually, more logical and foreseen results were obtained.

In addition to all of that, TOGG was expected to start mass production in the first quarter of 2023, and the number of EVs produced by the end of 2023 was predicted to be 18,000 [38]. Thus, a burst in demand was expected, since the authorized people issued a sales guarantee. For this reason, the number provided by TOGG was added to the forecasted EV numbers to achieve better and more applicable results in the second step, which was charging station deployment. The additional procedure was parallel to the seasonality of the overall sales. The seasonality coefficient was multiplied monthly by the number of EVs that TOGG promised.

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

Figures 2 and 3 illustrate the results obtained for 24 and 36 months, respectively. The results provided in the tables below were obtained from the estimation approach carried out with the GLM. The reason behind choosing the GLM was to observe the minimum sMAPE and MAE values, which are provided in Table 1. Several fluctuations were monitored in the forecasted EV sales results, which were expected because of the nature of vehicle sales in Türkiye. For past sales, usually an extreme increase in the last two months of the year and a dramatic decrease at the beginning of the year were seen. Correspondingly, the forecasting approach resulted in a similar pattern. As a result, it is expected that there will be approximately 115,000 EVs in Türkiye by the end of 2025. The evaluation metrics were defined and the working principle was explained previously. Here, the error rates obtained are provided in Table 1.

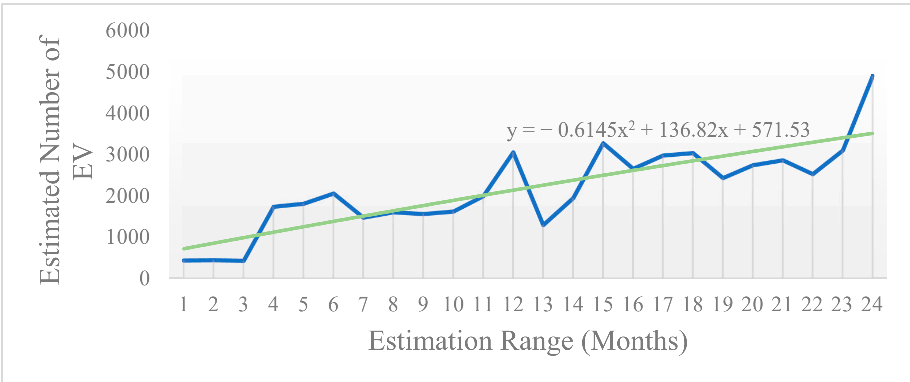

Figure 2. Forecast results for 24 months.

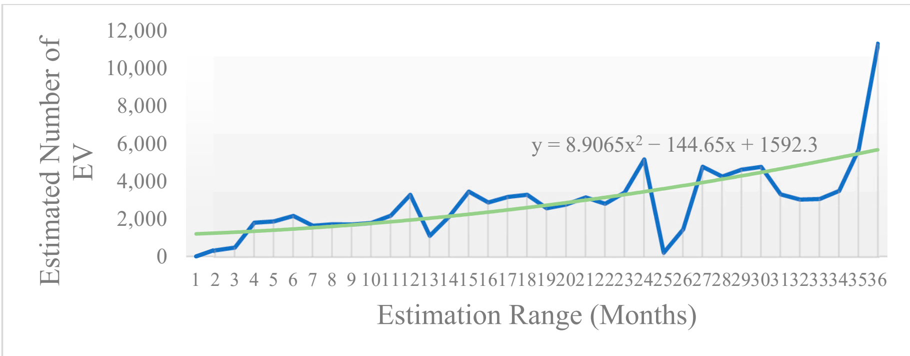

Figure 3. Forecast results for 36 months.

Table 1. Error rates of the applied models.

Applied Model	sMAPE	MAE	RMSE
Generalized linear model	10.4103	8320.3053	11,079.5156
Multivariate regression	11.8479	8408.8946	10,345.3683
Theta	11.9579	8451.3415	10,487.4450
Generalized least square	12.9192	9509.9190	12,028.0517
Random walk (last value naïve)	13.0060	9632.6875	12,560.9452
Random walk (average value naïve)	13.2313	9654.6477	12,169.0684
Random forest regressor	13.3869	9956.4972	12,637.5304
Random walk (constant naïve)	13.3905	9959.4583	12,641.1236
Random walk (seasonal naïve)	13.3908	9610.7083	12,099.2996
ARIMA (7, 2, 4)	13.3908	9959.7083	12,641.4682
Exponential smoothing	13.3908	9959.7327	12,641.5018
Autoregressive distributed lag	13.4503	10,013.4996	12,721.6936

3. Location Selection Approach

The main objective of this study was to meet the demand of customers, which is to provide EV charging services between cities, while minimizing the station placement and charging installation costs. For this purpose, the candidate places to be analyzed were selected. Therefore, the highways under control of the government, which are Ankara–stanbul, Aydın–İzmir, Mersin–Adana, and Osmaniye–Şanlıurfa, were chosen. Optimization approaches were applied. Data gathering and preprocessing, the proposal of the approach, and the results are discussed in this section.

3.1. Data Gathering and Preprocessing

The selected highways include numerous different entrances that divide them into several parts. As this study aimed to offer places to deploy charging stations, parts of these highways needed to be well defined. Parts were determined as stretches of road between two consecutive gates.

Tables 2–5 show the following information based on each highway part: the daily average number of passenger cars; the ratio of the daily average number of cars passing by to the total number of passenger cars, extended to years; the averages of the calculated ratios; and the expected daily number of EVs traveling. The daily number of cars traveling between highway parts was retrieved from the General Directorate of Highways' annual reports [39–42]. On the other hand, the yearly total number of passenger cars in Türkiye was used to discover the proportions of cars passing through highways [43–46]. The calculation of the proportions was carried out by dividing each entry by the total number of passenger cars. Lastly, the number of expected EVs on the highways was computed by using the average ratios and the estimated number of total EVs in Türkiye up to 2025, as in the Forecasting Approach section.

As indicated in the tables above, there are 15, 5, 6, and 12 parts on the Ankara–İstanbul, Aydın–İzmir, Mersin–Adana, and Osmaniye–Şanlıurfa highways, respectively. The implication of these numbers is that the candidate locations for charging stations are between these parts. For better understanding, the following example is provided:

- The last row of Table 5 is the last part of the Osmaniye–Şanlıurfa highway: Suruç–Şanlıurfa;
- The daily average number of passenger cars on this part was 7554 in 2021, and the total number of passenger cars in Türkiye was 13,710,272 in 2021;
- The daily average of the total number of passenger cars was 0.06%;
- The same procedure applied for 2020, 2019, and 2018;
- The average proportion is the arithmetic mean of the ratios of the years in the same rows;
- The expected number of EVs is the output of multiplying the average proportion and the forecasted number of EVs, as stated in Section 3 of this study.

Studies in the field of transportation are usually carried out while considering the rush hours. Therefore, the charging station location problem should be solved based on the rush hours. To calculate the density during rush hour, the expected daily number of electric vehicles, as in Tables 2–5, was divided into 24 to find the hourly rate of the number of EVs passing by. Then, the output was multiplied by two, which is a general assumption according to TOMTOM of the rush hour density [47]. In addition, people who own an EV are generally willing to recharge their vehicle when the SoC (state of charge) is below 30% [48]. Because of this, the SoCs of EVs on the highway parts were divided evenly into four classes: less than 30%, between 30 and 45%, between 45 and 60%, and more than 60%. The resulting numbers for the SoC of less than 30% indicate the number of EVs that require charging on the given highway parts, which is demonstrated in Table 6 below. The parts were numbered based on the numbering in Tables 2–5.

Table 2. Related dataset of the Ankara–İstanbul highway.

	2021		2020		2019		2018			
	Total Passenger Cars 13,710,272		Total Passenger Cars 13,110,657		Total Passenger Cars 12,504,767		Total Passenger Cars 12,393,329			
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 EVs**
Doğu İzmit–Sapanca	29,118	0.21%	29,539	0.23%	33,918	0.27%	36,295	0.29%	0.25%	288
Sapanca–Adapazari	28,482	0.21%	28,928	0.22%	33,321	0.27%	35,314	0.28%	0.24%	282
Adapazari–Akyazi	22,771	0.17%	22,847	0.17%	27,024	0.22%	27,046	0.22%	0.19%	223
Akyazi–Hendek	22,445	0.16%	21,652	0.17%	25,617	0.20%	25,569	0.21%	0.19%	213
Hendek–Düzce	21,638	0.16%	20,935	0.16%	24,559	0.20%	23,256	0.19%	0.18%	202
Düzce–Kaynaşli	19,812	0.14%	19,117	0.15%	23,221	0.19%	21,598	0.17%	0.16%	187
Kaynaşli–Abant	19,566	0.14%	18,562	0.14%	22,539	0.18%	20,984	0.17%	0.16%	182
Abant–Bolu Bati	20,032	0.15%	19,203	0.15%	23,417	0.19%	21,450	0.17%	0.16%	188
Bolu Bati–Bolu Doğu	19,335	0.14%	18,574	0.14%	22,457	0.18%	20,518	0.17%	0.16%	181
Bolu Doğu–Yeniçağa	19,844	0.14%	19,194	0.15%	23,166	0.19%	21,262	0.17%	0.16%	186
Yeniçağa–Dörtdivan	19,847	0.14%	19,043	0.15%	22,527	0.18%	20,987	0.17%	0.16%	184
Dörtdivan–Gerede	19,987	0.15%	19,084	0.15%	22,665	0.18%	20,899	0.17%	0.16%	184
Gerede–Çamlidere	15,748	0.11%	14,233	0.11%	17,780	0.14%	15,904	0.13%	0.12%	142
Çamlidere–Çeltikçi	16,241	0.12%	14,806	0.11%	17,712	0.14%	16,327	0.13%	0.13%	145
Çeltikçi–Akincilar	16,807	0.12%	15,420	0.12%	18,338	0.15%	16,872	0.14%	0.13%	150

Table 3. Related dataset of the Aydın–İzmir highway.

	2021		2020		2019		2018			
	Total Passenger Cars 13,710,272		Total Passenger Cars 13,110,657		Total Passenger Cars 12,504,767		Total Passenger Cars 12,393,329			
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 EVs**
Işikkent–Tahtaliçay	35,670	0.26%	30,451	0.23%	32,322	0.26%	32,711	0.26%	0.25%	292
Tahtaliçay–Torbali	32,789	0.24%	28,122	0.21%	30,578	0.24%	30,092	0.24%	0.24%	271
Torbali–Belevi	24,839	0.18%	20,553	0.16%	23,678	0.19%	23,831	0.19%	0.18%	207
Belevï–Germencïk	20,296	0.15%	18,965	0.14%	19,657	0.16%	19,461	0.16%	0.15%	174
Germencïk–Şevketïye	18,005	0.13%	16,213	0.12%	17,667	0.14%	16,997	0.14%	0.13%	153

Table 4. Related dataset of the Mersin–Adana highway.

	2021		2020		2019		2018			
	Total Passenger Cars 13,710,272		Total Passenger Cars 13,110,657		Total Passenger Cars 12,504,767		Total Passenger Cars 12,393,329			
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 EVs**
Serbest Bölge–Tarsus	21,634	0.16%	19,358	0.15%	22,068	0.18%	18,295	0.15%	0.16%	181
Tarsus–Çamtepe	20,275	0.15%	18,266	0.14%	20,758	0.17%	17,100	0.14%	0.15%	170
Çamtepe–Yenïce	21,343	0.16%	19,300	0.15%	21,937	0.18%	18,108	0.15%	0.16%	180
Yenïce–Adana Bati	27,158	0.20%	25,467	0.19%	28,475	0.23%	23,375	0.19%	0.20%	232
Adana Doğu–Ceyhan	20,083	0.15%	16,572	0.13%	18,436	0.15%	17,216	0.14%	0.14%	161
Ceyhan–İskenderun Ayr. Bati	19,389	0.14%	16,222	0.12%	18,058	0.14%	16,887	0.14%	0.14%	157

Table 5. Related dataset of the Osmaniye–Şanlıurfa highway.

	2021		2020		2019		2018			
	Total Passenger Cars 13,710,272		Total Passenger Cars 13,110,657		Total Passenger Cars 12,504,767		Total Passenger Cars 12,393,329			
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 EVs**
Toprakkale–Osmanïye	14,323	0.10%	11,664	0.09%	12,502	0.10%	11,776	0.10%	0.10%	112
Osmanïye–Düzïçï	15,370	0.11%	12,696	0.10%	13,628	0.11%	12,769	0.10%	0.11%	121
Düzïçï–Bahçe	15,003	0.11%	12,373	0.09%	13,309	0.11%	12,421	0.10%	0.10%	118
Bahçe–Nurdaği	14,035	0.10%	11,505	0.09%	12,363	0.10%	11,543	0.09%	0.10%	110
Nurdaği–Narli	12,054	0.09%	9699	0.07%	10,427	0.08%	9654	0.08%	0.08%	93
Narli–Gazïantep Bat	11,386	0.08%	9034	0.07%	9780	0.08%	8990	0.07%	0.08%	87
Gazïantep Bati–Gazïantep Kuzey	8126	0.06%	6351	0.05%	6466	0.05%	6094	0.05%	0.05%	60
Gazïantep Kuzey–Gazïantep Doğu	8075	0.06%	6097	0.05%	5998	0.05%	5570	0.04%	0.05%	57
Gazïantep Doğu–Nïzïp	10,348	0.08%	8941	0.07%	10,009	0.08%	8860	0.07%	0.07%	85
Nïzïp–Bïrecïk	8436	0.06%	6442	0.05%	7030	0.06%	6243	0.05%	0.05%	62
Bïrecïk–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

Table 6. Expected demand of every highway for each part.

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 necessary information for this study was the ranges of existing EVs. Without considering the ranges, the mathematical model and its results would be irrelevant and useless.

Brands have different strategies for EV batteries. Some seek long-distance coverage, but several of them aim to offer lighter vehicles. Even the same brand can have different market plans for different models. Therefore, different brands and models were considered. In Table 7, it can be seen that the ranges varied within each brand and model [36]. The ranges had a non-negligible effect on the results: They changed the constraint status, which also directly affected the customer satisfaction level.

Table 7. Range information of several brands and models [36].

Brand and 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

3.2. Mathematical Model

In this section, a mathematical model is provided to solve the current problem. The following content is an explanation of the data, the assumptions made before running the mathematical model, notations and their definitions, and, finally, the formulation.

3.2.1. Assumptions of the Mathematical Model

A model is a representation of the real world to gain a better understanding of actual situations [49]. Therefore, to solve a real-world problem, some key assumptions need to be made. To solve the problem in this study, several assumptions were made. These assumptions are as follows:

- Drivers do not have extraordinary driving style;
- EV driving ranges are constant and invariable;
- The average range of the included EV models is applicable for every customer;
- Neither electric trucks nor electric motorcycles exist in the system;
- The electricity in the charging system is not finite and is not interruptible;
- No line forms in front of the charging stations.

3.2.2. Modeling

Sets/Indices
i parts of the highways i = {1, 2, 3, . . ., n},
Data/Parameters
S: cost of construction of a new charging station (USD);
C: cost of a charger installation in a station (USD);
P: penalty cost of an unsatisfied charging demand (USD);
I: maximum number of stations that can be placed;
T: maximum number of chargers that can be installed in a station;
M: a big number;
D_i*: charging demand on highway part i.*
Decision Variables
X_i *= {1, if highway part i is selected for an EV charging station; 0, otherwise};*
CH_i *= number of chargers installed at highway part i;*
UD_i *= number of unsatisfied charging demands on highway part i;*
ND_i *= number of updated demands on highway part i.*

3.2.3. Formulation

Objective Function

$$z^* = minz = \sum_i^n (S \cdot X_i + C \cdot CH_i + P \cdot UD_i) \tag{1}$$

Objective Function (1) is to minimize the total cost, which consists of the construction of a charging station, the installation of chargers in the given station, and the penalty cost of unsatisfied charging demands on the given highway. Ordinarily, the most desired outcome is to have maximum customer satisfaction with minimum cost, which is the first necessity of the study.

Constraints

$$M \cdot X_i \geqslant CH_i \quad \forall i \tag{2}$$

$$\mathrm{CH}_i \geqslant X_i \quad \forall i \tag{3}$$

Constraint (2) defines that no chargers are placed if there are no stations on highway part *i*. The reason for this constraint is that no charger can be established intuitively in a station that has not been selected. Constraint (3) prevents the model from selecting a place as a charging station that does not have any charging capacity. Constraint (3) also ensures that decision variable X_i takes a value of 1 if the chargers are located there. On the other hand, it also archives and lists the chosen locations.

$$D_i - CH_i = UD_i \quad \forall i \tag{4}$$

$$ND_i = D_i + UD_{i-1} \quad \forall i (i \neq 1) \tag{5}$$

$$ND_i - CH_i = UD_i \quad \forall i \tag{6}$$

Constraints (4)–(6) are about demand limitations and updating processes. Constraints (4) and (6) define unsatisfied charging demands, and the values that these constraints yield as outputs are kept as results in a database. Constraint (5) updates the demand when the whole demand for the last part of the highway is not met.

$$\sum_i^n X_i \leqslant I \tag{7}$$

$$X_i - X_{i-1} \leqslant 1 \qquad \forall i (i \neq 1) \tag{8}$$

$$CH_i \leqslant T \qquad \forall i \tag{9}$$

Constraints (7)–(9) are prevention constraints, where Constraint (7) ensures that the model does not yield more than the indicated number of candidate locations, Constraint (8) states that two consecutive parts cannot both have a station, and Constraint (9) prevents the model from installing more chargers than desired. The existence of Constraint (9) ensures that the electricity limit of the infrastructure is not exceeded.

$$X_i \in \{0, 1\} \qquad \forall i \tag{10}$$

$$CH_i, UD_i, ND_i \in \mathbb{N} \qquad \forall i \tag{11}$$

Constraints (10) and (11) define variables. These constraints ensure that X_i is a binary constraint and that CH_i, UD_i, and ND_i can take values as natural numbers, respectively.

3.2.4. Results of the Mathematical Model

The formulation in Section 3.2.3 was examined by using Python software 3.11.3 as an optimization tool. The formulation and constraints were coded properly to the platform, runs were taken, and all of the results obtained were optimal.

There were four total runs for the whole process because the number of applicable highways was four. The obtained results are shared in the following Tables 8–11. The tables consist of the highway names, part indicators, and decision variable outputs of the model.

Table 8. Results of the variables of the 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

Table 9. Results of the variables of the 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

Table 10. Results of the variables of the 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

Table 11. Results of the variables of the 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

Throughout the 15 parts of the Ankara–İstanbul highway, the resulting station placement offer was five, whereas the total number of chargers at those stations was 37. With the construction cost, the charger installation cost, and the penalty for unsatisfied charging demands, the total cost turned out to be USD 914,550.

The Aydın–İzmir highway, which contained the lowest number of parts, yielded an offer to construct just two stations. Along with these two stations, 14 chargers were suggested to be installed, and the end cost was USD 401,900.

The third analyzed highway was the Mersin–Adana highway, and the total cost of station construction and charger installation and the penalty costs for unsatisfied demands ended up being USD 392,000. For this highway, the mathematical model suggested constructing two stations with eight installed chargers each.

Even though the Osmaniye–Şanlıurfa highway has many parts, low demand occurred because the number of vehicles using this highway was not many, which led the model to offer fewer stations to satisfy the charging demand. As shown in Table 11, the number of stations suggested to be constructed was three, with seven, six, and four chargers, respectively. As a result, the overall cost turned out to be USD 487,600.

4. Discussion and Future Prospects

In this study, various approaches are presented for the locations of EV charging stations and the number of chargers required for vehicles expected to need charging on state-controlled highways. In this process, analyses were carried out on the daily average number of vehicles using the highway parts. In order to advance these studies, it is planned to expand the current study with the time stamp data of the 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 would be beneficial to include the lengths of the highway segments and thus add different scenarios about the SoC situations of EVs to the study. Thanks to these future scenarios, it is foreseen that different alternatives can be created for charging service providers and steps can be taken to increase the satisfaction of EV users.

Moreover, the current assessment of electric vehicles (EVs) fails to consider individual range variations; instead, an average is applied uniformly across all models. Nevertheless, a more nuanced approach can be adopted within the study's framework by incorporating variable ranges specific to each EV. This proposed modification promises a more accurate depiction of the results, enhancing their practicality and reliability for real-world applications.

Another variant could be to apply simulation-based approaches by analyzing the density of the roads. This way, probabilistic situations can be better observed, and bottlenecks and stochasticity can be considered while offering the best sites for EV charging stations. Several studies have also explored the development of real-time simulations for EV stations, employing the high-speed FPGA computation platform [50–54] to assess the overall operational efficiency [55].

5. Conclusions

In conclusion, this research delves into the critical issue of developing an optimal electric vehicle (EV) charging infrastructure in Türkiye, with a specific focus on highways and intercity travel demands. The increasing global interest in EVs, with Türkiye's commitment to phasing out traditional vehicles by 2035, necessitates a specialized approach for Türkiye. The study's primary motivation is rooted in the imminent surge in EV usage, especially with Türkiye's Automobile Joint Venture Group (TOGG) having been set to commence mass production in 2023.

This study comprises two main parts: forecasting and location selection. In the forecasting phase, a novel approach is introduced to predict future EV numbers by developing forecast models for overall car sales and internal combustion engine car sales. The results indicate an expected 115,000 EVs in Türkiye by the end of 2025. This forecasting approach not only addresses the scarcity of monthly precision EV sales data but also considers the impact of external factors such as the COVID-19 pandemic and TOGG's production plans.

The results of the location selection model propose strategic locations and quantities of charging stations for four state-controlled highways in Türkiye. The optimal placement and number of stations vary based on the demand patterns and specific characteristics of each highway. The study recommends constructing 12 charging stations with 37 chargers on the Ankara–İstanbul highway, 2 stations with 14 chargers on the Aydın–İzmir highway, 2 stations with 8 chargers on the Mersin–Adana highway, and 3 stations with a total of 17 chargers on the Osmaniye–Şanlıurfa highway.

Key findings from this research highlight the importance of adapting charging infrastructure optimization approaches to Türkiye's unique circumstances. The study contributes not only to the ongoing conversation about sustainable transportation but also offers practical solutions to meet the growing demand for EVs in Türkiye. As electric vehicle usage continues to rise, the proposed strategies aim to alleviate range anxiety, enhance customer satisfaction, and foster widespread adoption of EVs in the country. The research question (In light of variables including future EV adoption, intercity travel patterns, and environmental sustainability, how can the best sites and numbers of electric car charging stations be strategically established in Türkiye to accommodate the growing demand for electric vehicles?) is addressed comprehensively through a multi-faceted analytical approach.

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