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Research Article

Empowering Electric Vehicle Adoption: Innovative Strategies for Optimizing Charging Station Placement Based on Projected Demand

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Electric vehicles (EVs) are pivotal for reducing transportation-related emissions; however, the lack of adequate charging infrastructure remains a significant barrier to their widespread adoption. This study presents a comprehensive methodology for optimizing EV charging station placement. It combines a gravity model, scenario analysis, and mixed-integer linear programming (MILP) to ensure a thorough and robust approach. The model aims to maximize accessibility by ensuring both path-level and overall system demand coverage across diverse scenarios, providing reassurance about the validity of the findings. The methodology is tested on the Bursa–İzmir motorway in Turkey, a strategic intercity route with rapidly growing EV penetration. Results reveal that the optimal configuration involves locating charging stations in seven of the nine service areas. This allocation secures a minimum path coverage ratio of 0.903, meaning 90.3% of the route is covered by charging stations, and an overall demand coverage ratio of 0.935, indicating that 93.5% of total demand is covered across all scenarios. A sensitivity analysis further shows that increasing the network to 45 chargers elevates reachability levels to above 97%, indicating the infrastructure scale required for reliable service quality. The findings underscore the practical applicability of the proposed framework, providing policymakers and infrastructure planners with robust, data-driven guidance for charging network expansion. By integrating demand forecasting with resilient optimization, this study advances both methodological and empirical insights, empowering the audience to make informed decisions for sustainable EV adoption.

Keywords: charging locations; electric vehicles; gravity model; mixed integer linear programming; random driving range; scenario analysis

1. Introduction

Electric vehicles (EVs) play a crucial role in global mitigation plans, with a significant increase in ownership supported by national policies. Several countries are advocating for the uptake of EVs, with governmental bodies offering subsidies to both manufacturers and consumers, as well as implementing various fiscal and nonfiscal motivations [1]. Projections indicate a substantial rise in EVs worldwide, with the number expected to range between 120 and 259 million by 2030 [2]. However, developing charging infrastructure, particularly in terms of location planning to match charging demand and power supply, remains a critical challenge. Inadequate charging facilities may lead to long queues. At the same time, an oversupply may result in the underutilization of charging stations [3].

Türkiye has an enormous potential market for the automobile sector due to the increase in population, urbanization, and industrialization. Türkiye's population is projected to reach 93 million by 2030. Accordingly, the number of passenger vehicles (EV and non-EV) is expected to reach 27.9 million by 2030. This will double the vehicle ownership in Türkiye from 154 vehicles per 1000 to around 300 per 1000 per capita [4]. In 2011, the first year electric cars were registered; there were 24 registered EVs, while this number reached 952 in 2018. The number of electric cars registered for traffic exceeded the 1000 mark in 2019, rising to 6267 in 2021, 14,552 in 2022, and 80,043 in 2023. By the end of last year, the number of electric cars registered for road use had increased by 129.6% compared to 2023, reaching 183,776 (Figure 1).

In line with the anticipated growth potential of EV demand in Türkiye, state incentives and regulations on EVs and related chargers have been prepared to address environmental concerns [6]. Additionally, academic studies on EV site selection are gaining prominence in the literature. For example, Gönül et al. [7] present a framework for EV charging station siting along highways, incorporating expert opinions from various disciplines. The method is tested on both a prototype highway and the heavily trafficked Edirne–Ankara highway.

This study proposes an integrated methodology for selecting the location and number of EV charging stations to better shape the future market. The main issue in the charging facility location selection problem is to provide an appropriate balance between the selected locations and the satisfaction of the charging demand. The nature of the EV charging station configuration problem necessitates solid EV demand projections. Accordingly, a hybrid approach based on the gravity model and scenario analysis is initially used to make different EV demand projections for various plausible states.

In the following stage, a novel mixed-integer linear programming (MILP) model is also built to maximize the expected reachability of EVs on their trips through a given road network. It is assumed that the driving ranges are random. To consider the initial battery level of the cars, different probability distributions for the driving range are utilized for cars exiting the road network and for those traveling between points within the road network. The final suggestions for station locations and capacities are based on the results of all scenarios. A sensitivity analysis is conducted to validate the model and determine the optimal number of chargers at each station.

The proposed methodology is applied to the Bursa–İzmir motorway, the second part of the İstanbul–İzmir motorway (coded as O5). O5 connects İstanbul (Türkiye's largest city) with İzmir (the third largest city) via Bursa (the fourth largest city). Although O5 is the most expensive motorway in Türkiye (~45 USD), it makes a significant economic contribution to road users by saving them time and fuel. This motorway is a prime candidate for intercity EV usage. Therefore, planning the location and size of charging stations plays an essential role.

This paper introduces three significant contributions. First, it proposes an integrated methodology for locating EV charging stations, offering a versatile and resilient approach to deploying infrastructure. Second, it addresses dual uncertainties, demand and driving range, employing scenario analysis and a novel linear modeling approach. Third, it applies the methodology to the Bursa–İzmir motorway, thus contributing theoretically and practically.

The rest of the paper is organized as follows: The second section provides a literature survey on EV demand forecasting and charging station location models. The third section provides the proposed methodology. In the fourth section, the proposed methodology applied to the Bursa–İzmir motorway of Türkiye is provided, the results are evaluated, and policy recommendations are suggested. Finally, in the last section, conclusions and further suggestions are given.

2. Literature Review

The literature is analyzed from two perspectives, corresponding to the two stages of the methodology. Initially, studies for EV demand forecasting are presented. Subsequently, EV charging station location models are reviewed.

2.1. EV Demand Forecasting Models. The surge in EV demand over the past decade has necessitated accurate forecasting models for optimal EV charging station placement. Existing literature showcases various methodologies, such as long-term forecasting, logit models, spatial analysis [8], structural equation modeling, and regression models [9]. There are also studies in the literature for demand response management of EVs for balancing demand and supply [10]. Moreover, as reviewed by Yang et al. [11], some studies focus on estimating charger infrastructure requirements and needed infrastructure investments.

Recent studies highlight the increasing use of sophisticated models for demand forecasting, which can be broadly grouped according to their underlying objectives and application domains. One major stream leverages advanced spatiotemporal deep learning models to predict short-term, operational EV charging load, typically at the station level within dense urban environments. For instance, Wang et al. [12] developed an adaptive spatiotemporal graph recurrent network (ASTGRN) to learn spatial correlations from EV trajectory data, while Jiang et al. [13] proposed a graph-based spatiotemporal attention network (G-STAN) to predict hourly demand fluctuations precisely. A second stream addresses long-term strategic planning by forecasting the aggregate quantity of infrastructure needed at a national level. A notable example is Zhang et al. [14], who used a hybrid deep learning model to forecast future EV sales and the corresponding required number of charging piles. While

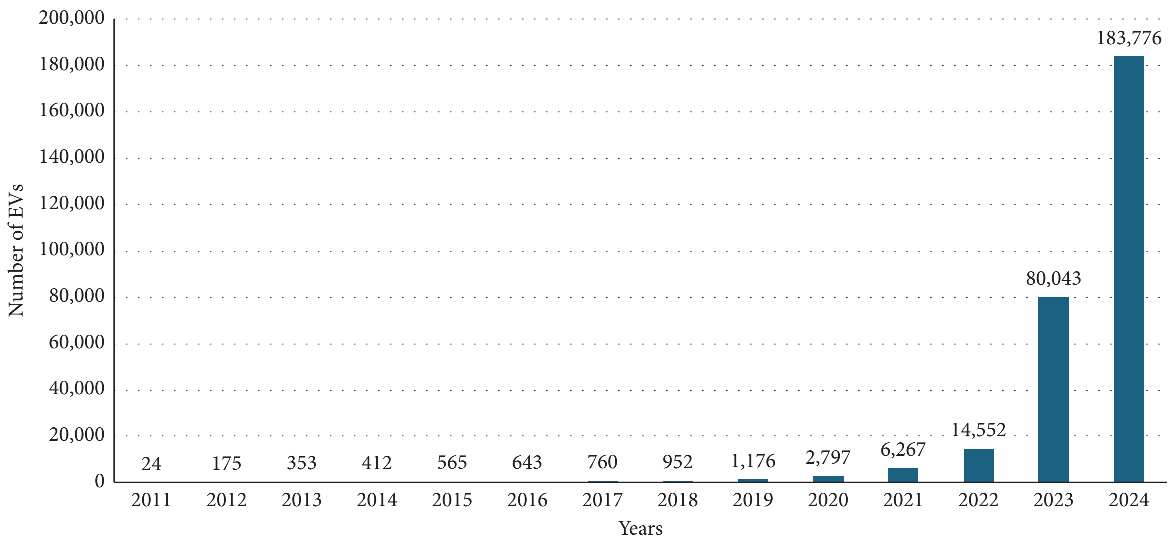

Figure 1: Number of registered EVs in Türkiye from 2011 to 2024 [5].

these advanced models are powerful for predicting operational load in data-rich urban settings or forecasting national trends, the strategic planning of charging infrastructure along intercity highway corridors presents a distinct challenge. This specific context is the focus of the present study and necessitates robust methods that can estimate potential travel flows between major population centers.

This study presents a novel approach, employing a gravity model and scenario analysis for demand projections. Unlike previous stochastic models, this approach transforms the problem into a deterministic framework, providing more robust and reliable predictions. Objective data from relevant sources address macroeconomic uncertainties, contributing to a better understanding of EV demand dynamics and advancing forecasting methodologies in EV adoption and charging infrastructure planning. Thingvad et al. [15] mention that installing chargers on private properties is an uncomplicated solution for powering EVs, potentially serving the needs of the majority of cars, by showing statistics from Denmark, which can also be generalized. However, for extended journeys, the availability of EV charging stations becomes essential.

2.2. EV Charging Station Location Models. The problem of EV charging stations has been a subject of scholarly interest for decades. Researchers have primarily addressed this problem by employing diverse mathematical frameworks, including maximal covering location problem (MCLP) [16, 17], flow capturing location problem (FCLP) [18, 19], flow refueling location problem (FRLP) [20], capacitated FRLP [21], deviation FRLP [22, 23], arc-cover path-cover FRLP [24], and p-median problem [25].

Within the FRLP framework, Kuby and Lim [20] use an MILP approach and solve the problem using the branch and bound method after extending the flow-capturing location model by incorporating the limited driving range of vehicles. In contrast, MirHassani and Ebrazi [26] reformulate the FRLP using a path segment approach and develop a flexible model that allows the decision-maker to choose between applying the set covering problem and the maximum covering problem. Additionally, Lee and Han [27] studied the FRLP under a stochastic driving range to determine the locations of EV refueling stations by using a mixed-integer nonlinear programming (MINLP) approach and applying a Benders-and-Price algorithm. Kadri et al. [28] address a multiperiod EV fast-charging station location problem with uncertain demand. Their approach employs a scenario tree-based multistage stochastic integer programming to maximize the expected value of satisfied demand.

In contrast to the FRLP perspective, Wu and Sioshansi [19] adopt an alternative methodology by presenting a stochastic flow-capturing location model to determine the optimal sites for EV fast-charging stations. They solve this model by decomposing via the sample-average approximation method and determine how the final solution deviates from the optimal solution by applying an averaged two-replication procedure.

There have been diverse perspectives on the problem. Notably, Li and Jenn [29] assess the spatial–temporal distributions of charging opportunities for drivers in California and develop an MILP model to determine the optimal placement of EV charging stations at home and nonhome locations, as well as the charging strategy of drivers. Yi et al. [30] developed a modified geographical PageRank model to forecast charging demand by defining the problem as a directed graph and utilizing trip origin–destinations (O–D) and social characteristics. Then, the demand forecast is entered into a capacitated MCLP to determine optimal station locations for EV charging stations, maximizing their utility. Finally, Li et al. [3] integrate EV charging station location and delivery route planning problems using a bilevel programming approach. A two-phase hybrid heuristic approach is employed, consisting of a two-layer genetic algorithm to solve the routing planning problem and simulated annealing for the location problem.

Recent contributions have advanced the field along two main fronts: integrated system planning and methodological diversification. A prominent trend is the co-optimization of charging stations with grid assets like renewable distributed generations and energy storage [31, 32], often utilizing multiobjective heuristic algorithms [33] or tractable MILP formulations [34] to manage complexity in coupled transportation–power networks [35, 36]. Concurrently, research has broadened beyond traditional optimization to include data-driven, geometric, and decision-science frameworks. For instance, studies have employed hybrid machine learning approaches based on user data [37], geometric models like Voronoi diagrams for strategic competitive siting [38], and multicriteria decision-making (MCDM) for sustainability-focused site evaluation [39].

Table 1 provides a comprehensive overview of studies, detailing their properties such as period, demand, demand forecast, model type, formulation, and method (exact or heuristic). The table's last row compares this study's properties with those identified in existing literature. Within the proposed model's framework, we build a single-period deterministic optimization model for demand projection. By incorporating scenario analysis and the gravity model within the structure of the MILP framework, the demand projection process's accuracy and robustness are enhanced.

Lee and Han [27] addressed a closely related issue without considering capacity, proposing a nonlinear programming model relying on reachability values. Their nonlinearity stems from multiplying these values, representing the probability of an EV traversing a link without running out of battery along successive arcs in a path to compute overall reachability. In contrast, our proposed model takes a distinct approach, introducing a linear model to address the same issue. This linear model maintains solution precision while determining optimal charger quantities and placements at each station. Additionally, nonlinearity is mitigated by modifying flow balance equations, ensuring that the incoming flow at the destination point of a link equals the product of the outgoing flow at the origin point and the link's reachability value.

A related study proposed an optimization-based fast-charging station deployment strategy, demonstrating how data-driven approaches can inform infrastructure expansion plans [40]. However, their model does not explicitly address reachability under stochastic driving range conditions or include scenario-based demand projections, as done in this study.

This study stands out for two primary reasons. Firstly, it employs a unique approach by integrating the gravity model and scenario analysis for demand forecasting, the advantages of which are elucidated in the preceding subsection. Secondly, the study utilizes an MILP formulation for a stochastic model type, which can be efficiently solved using readily accessible solvers without requiring specialized treatments such as Benders decomposition or genetic algorithm.

3. Proposed Methodology

The study is conducted in two main stages: (1) EV demand projection and (2) charging station planning, which includes the location selection for the stations and determining the number of EV chargers at the stations. The flowchart of the proposed methodology is given in Figure 2.

Since the EV charging station location model requires an appropriate demand projection, the first stage, including a gravity model and scenario analysis, is conducted. To cope with the uncertainty underlying macroeconomic conditions and transform the problem's stochastic nature to a deterministic one, a scenario analysis was conducted to generate alternative future pictures [50]. The scenarios generated are then given as input to the gravity model.

Originating from the physics concept of gravity, the gravity model serves as a core analytical tool for examining spatial relationships between variables. Initially employed to model international trade [51, 52], it was subsequently adapted to forecast travel demand across various transportation models [53–56]. In its standard form, the model estimates the flow between two points as a function of their populations, economic sizes, and the distance separating them [57]. We have selected the gravity model for this study because its reliance on population and distance aligns directly with our objective to estimate demand. Furthermore, its continued successful application in recent transportation demand forecasts [58, 59] strongly supports its validity for our analysis.

As the last step of the hybrid approach, a final set of scenarios is created, depending on the gravity model's results.

The second stage includes constructing the mathematical model needed to find the proper locations of EV charging stations according to the results of the first stage. The MILP model constructed considers all the demand scenarios found in the first stage and the randomness in the driving range. Sensitivity analysis is conducted to find the optimal numbers of some parameters, such as the number of chargers to be built.

3.1. Developed Model for EV Demand Projection.

The study's initial phase focuses on forecasting EV demand, with literature revealing various methods. Notably, Kadri et al. [28] and Wu and Sioshansi [19] employ scenario analysis, while Quddus et al. [42] and Quddus et al. [43] use Monte Carlo simulation-based scenario analysis. Yi et al. [47] adopt a queuing model for stochastic demand, and others employ gravity, logit, and regression models for deterministic demand. Additionally, as reviewed by Fescioglu-Unver and Yıldız Aktaş [60], machine learning models are applied in EV infrastructure planning. However, due to their need for large datasets, machine learning models are less suitable for cases with limited data availability.

This study adopts a hybrid approach to project demand accurately, combining a gravity model with scenario analysis. Scenario analysis is chosen to address future uncertainty by creating multiple plausible scenarios, aligning with Nguyen and Dunn's [50] perspective. A morphological analysis is used to create the scenario. First, the variables that define the system and possible states for each variable are identified. Second, the configurations are created by

Table 1: Summary of the literature review and the contributions of the proposed methodology used in this research.

Reference	Period	Demand	Demand forecast	Problem	Model type	Formulation	Method	
							Exact	Heuristic
[28]	Multi	Sto.	Scenario tree	FRLP	Sto. (travel range, demand)	ILP	Benders	GA
[19]	Single	Sto.	Scenario tree	FCLP	Sto. (demand)	MILP	Benders	
[27]	Single	Det.	Gravity model	FRLP	Sto.(travel range)	MINLP	Benders-and-Price	
[41]	Multi	Det.	Different demand profiles	FRLP	Det.	MILP	Multiperiod optimization	Myopic
[20]	Single	Det.	Gravity model	FRLP	Det.	MILP	Solver*	
[26]	Single	Det.	Gravity model	FRLP	Det.	MILP	Solver*	
[42]	Multi	Sto.	Monte Carlo simulation-based scenario analyses	EV charging station expansion decisions and hourly operational decisions over a prespecified planning horizon	Sto. (demand)	MINLP	Sample average approximation algorithm and progressive hedging algorithm	Local and global heuristics and rolling horizon heuristics
[43]	Multi	Sto.	Monte Carlo simulation-based scenario analyses	EV charging station expansion decisions and hourly operational decisions over a prespecified planning horizon	Sto. (demand)	MINLP	Hybrid decomposition algorithm	Local and global heuristics and rolling horizon heuristics
[44]	Multi	Det.	Optimization model	Resource allocation	Det.	MILP	Solver*	
[45]	Single	Det.	Predicted statistically from the relevant demographic and socioeconomic data	FRLP	Det.	MINLP	Branch and bound algorithm and label-correcting algorithm	
[46]	Single	Det.	Cross-nested logit models	FRLM	Det.	MIP	Branch and bound algorithm	
[47]	Single	Sto.	Queuing model	EV charging station location and capacity determination	Sto.	Multiobjective programming		Artificial immune algorithm
[48]	Single	Det.	GIS and logistic regression	MPRLM	Det.	MILP		Greedy-adding based heuristic
[29]	Multi	Det.	Based on travel diary data	Integrated EV charging optimization problem	Det.	MILP	Solver*	
[30]	Single	Det.	Modified geographical PageRank model	Capacitated MCLP	Det.	MILP	Solver*	

Table 1: Continued.

Reference	Period	Demand	Demand forecast	Problem	Model type	Formulation	Method	
							Exact	Heuristic
[49]	Single	Det.	Based on travel diary data	EV charging station location based on drivers' charging choice	Det.	IP		GA
[3]	Single	Det.	Based on travel diary data	EV charging station location and route planning	Det.	Bilevel programming		GA and simulated annealing
[31]	Single	Det.	Static load	Location and sizing of EVCS and RDGs	Det.	Multiobjective programming		PSO, Cuckoo Search
[33]	Multi	Det.	Predefined profile	Allocation and sizing of EVCS, DGs, and V2G	Det.	Multiobjective programming		SAMPE-JAYA, GA
[37]	Single	Det.	Census data	Allocation based on resident dispersion	Det.	Optimization and clustering		Hybrid GA and K-means
[36]	Multi	Sto.	Probabilistic	Location and sizing of EVCS and DGs in coupled TN–DN	Sto.	Multiobjective (fuzzy)		PSO
[32]	Multi	Det.	Scenario-based	Planning and sizing of solar EVCS with ESS	Technoeconomic	Simulation-based optimization		HOMER Algorithm
[39]	Single	Implicit	Expert opinion	Sustainability-based site selection/ranking	Decision sciences	MCDM		DEMATEL, COPRAS
[38]	Single	Implicit	Geometric (proximity)	Optimal location using proximity to competitors	Geometric	Voronoi diagrams	Geometric algorithm	
[35]	Multi	Det.	Predefined profile	Location in solar microgrid for loss reduction	Det.	Optimal power flow		PSO
[34]	Multi	Det.	Load factor curve	Placement of EVCS with V2G	Det.	MILP	Solver*	
The current study	Single	Det.	Gravity model and scenario analysis	FRLP	Sto. (travel range)	MILP	Solver*	

Note: COPRAS: Complex Proportional Assessment; DEMATEL: Decision-Making Trial and Evaluation Laboratory; Det.: Deterministic; MPRLM: Multipath refueling location model; Sto.: stochastic; V2G: vehicle-to-grid.

Abbreviations: DG, distributed generation; ESS, energy storage system; EVCS, electric vehicle charging station; FCLP, flow capturing location problem; FRLP, flow refueling location problem; GA, genetic algorithm; HOMER, hybrid optimization of multiple energy resources; IP, integer programming; ILP, integer linear programming; MCDM, multicriteria decision-making; MCLP, maximal coverage location problem; MILP, mixed-integer linear programming; MINLP, mixed-integer nonlinear programming; MIP, mixed-integer programming; OPF, optimal power flow; PSO, particle swarm optimization; SAMPE-JAYA, Self-Adaptive Multi-Population Elitist JAYA; TN–DN, transportation network–distribution network.

*The problem is solved using a commercial solver, e.g., CPLEX and Gurobi.

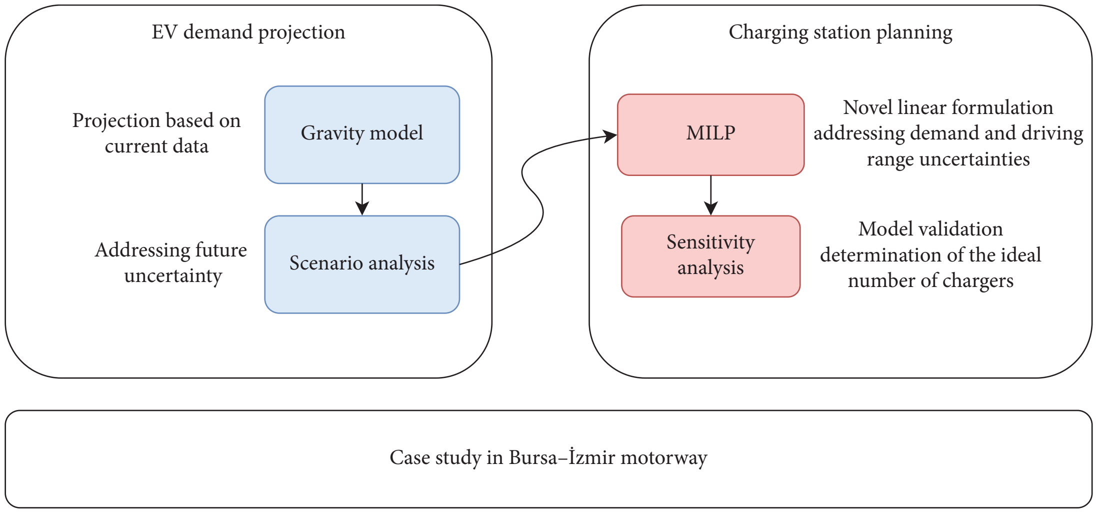

FIGURE 2: Flowchart of the proposed methodology.

matching each state of each variable with a state from another variable, forming a potential future picture called a scenario. Then, using the gravity model in the case study, the total number of cars passing through the Bursa–İzmir motorway is calculated for each of the nine scenarios created in the previous step.

As the last step of the demand forecast, the morphological scenario analysis is used for the second time to generate the final set of scenarios obtained from the previous scenarios by incorporating three different EV shares. This way, different demand projections for EVs using the motorway are obtained to feed the integer programming model in the second phase.

3.2. Developed Model for EV Charging Station Location Specification. In the second stage of this study, a new mathematical model is developed to find the locations of stations and the charging capacity (i.e., number of chargers) in the selected locations based on the predicted EV demands for each scenario. This mathematical model is based on an expanded network obtained from the original road network, which is critical to determining the stations that vehicles will visit following the possible paths. Moreover, the reachability phenomena are incorporated into the proposed mathematical model by modifying the standard flow balance equations, which enables a linear formulation. The details are given in the following sections.

3.2.1. Deriving the Expanded Network. In the proposed methodology, an approach followed by Lee and Han [27] is used to derive the expanded network. The main differences are that a linear formulation is developed as opposed to a nonlinear model used in that study, and different scenarios are considered for the demands of the possible paths in the road network. The linear formulation of the current study makes the solution much easier to obtain compared to Lee and Han [27].

A motorway network denoted as $G(N, A)$ that includes the origin and destination points and candidate points for EV charging stations (N) and road connections among them (A) is considered. The distance between point i and point j is represented as l_{ij}. For each O–D pair for which demand is estimated under various scenarios, the shortest path and the associated O–D pair to that path are found. In this way, a set of paths P is defined. Demands for the O–D pairs are also attached to the paths, and the demand of path p in scenario s is defined as d^{sp}.

For each path $p \in P$, an expanded network $G_p(N_p, A_p)$ is constructed. Let o_p and d_p be the origin and destination points of path p, respectively, and I_p be the set of candidate points on path p. Then, the following variables are defined:

$$N_p = \{o_p, d_p\} \cup I_p \text{ and } A_p = \{(i, j) | i \in N_p \backslash d_p,\ j \in N_p \backslash o_p \text{ and point } j \text{ comes after point } i \text{ on path } p\}. \quad (1)$$

A demonstration of the expanded network is given in Figure 3(b). In Figure 3(a), a path is given with its origin, its destination, and three candidate points. The expanded network is constructed, using the same set of nodes as the original path, and new arcs are added from each node to the nodes that follow it. After constructing the expanded network $G_p(N_p, A_p)$ for every $p \in P$, the expanded network $G'(N, A')$ is created as the union of all G_p such that $A' = \cup_{p \in P} A_p$.

The proposed mathematical model defines the flows on the arcs of the expanded network $G'(N, A')$. The flow on an arc (i, j) represents the number of vehicles that stop at point

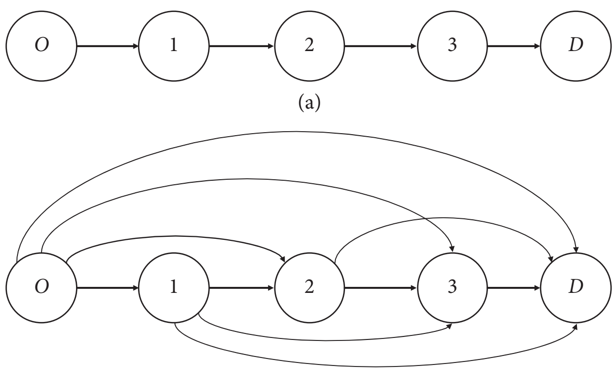

Figure 3: A demonstration of the expanded network. (a) Path p. (b) Expanded network $G_p(N_p, A_p)$ for Path p.

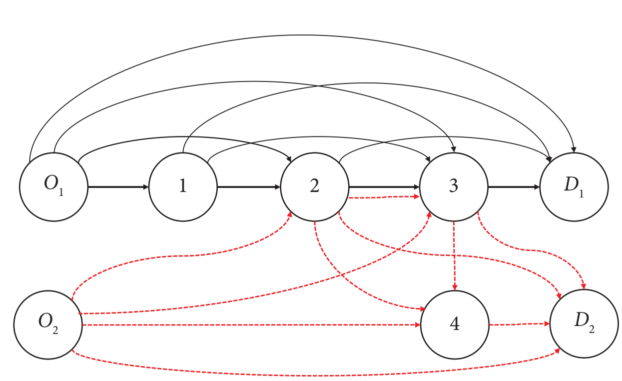

Figure 4: Expanded network $G'(N, A')$ for paths p_1 (black lines) and p_2 (dashed red lines).

i for charging, stop at point j for the subsequent charging, and skip all points in between i and j.

Supposing that there are two paths such as Path 1: $O_1 \longrightarrow 1 \longrightarrow 2 \longrightarrow 3 \longrightarrow D_1$ and Path 2: $O_2 \longrightarrow 2 \longrightarrow 3 \longrightarrow 4 \longrightarrow D_2$, then the expanded network will be as in Figure 4.

3.2.2. The Reachability Formulation. The reachability of a link (i, j), denoted as r_{ij}, is defined as the probability that a random vehicle will traverse the link without running out of battery. Mathematically, $r_{ij} = P\{R_{ij} > l_{ij}\}$, where l_{ij} is the link length and R_{ij} is the random variable representing the driving range of a random vehicle that traverses link (i, j) after starting its journey (possibly following a recharge) at point i. We assume that the distribution of R_{ij} may be dependent on the starting point i and the specific link (i, j) being traversed. If the starting point i is an origin point, R_{ij} represents the inherent variability in the initial charge levels of vehicles entering the motorway network, noting that these vehicles do not necessarily start with fully charged batteries. If the starting point i is a candidate point, the link is traversed after a potential recharge at point i. In this case, R_{ij} still accounts for charge variability as vehicles may not be fully recharged, and even fully charged ranges will vary depending on the vehicle model, degradation, and other factors. Furthermore, since R_{ij} is also dependent on the specific characteristics of the motorway segment between points i and j, this random variable captures link-related uncertainty. This is reasonable because, for instance, a fully charged car will exhibit different driving ranges on roads with varying average slopes.

Reference [27] computes a reachability index for each path using the reachability values of individual links and a constraint set leading to nonlinearity. Then, this index is multiplied by the demand value of the path in the objective function to compute the expected total covered demand (reaching the destination point without getting out of battery) of the path. In the formulation, the covered flow of each link, which is reflected in the model, is considered as the difference between the outgoing flow of the initial point and the incoming flow of the ultimate point of a link. It is assumed that if r is the reachability of a link with an initial flow value of f, then the flow value at the other end of the link is rf. When the flow balance equations are modified accordingly (as done in equation (2)), it is easy to see that the incoming flow of the destination point of a path is equal to the expected covered demand of that path and that the resulting formulation is linear. For instance, in the example expanded network in Figure 5, suppose that the vehicles using this path will stop at Points 2 and 3 for charging. Thus, the selected links are $(O, 2)$, $(2, 3)$, and $(3, D)$, and the expected covered demand should be equal to $r_{O2}r_{23}r_{3D}d$ given that d is the demand value of the path. In the formulation, the outgoing flow of point O is d, the incoming and outgoing flows of Point 2 is $r_{O2}d$, the incoming and outgoing flows of Point 3 is $r_{O2}r_{23}d$, and the incoming flow of Point D is $r_{O2}r_{23}r_{3D}d$ as desired. In the following mathematical model in the subsection, the flow on a link (i, j) on path p under scenario s is denoted by the variable y_{ij}^{sp}, and the expected covered demand of path p under scenario s is denoted by h^{sp}. Therefore, for the example in Figure 3, the following relations are obtained:

$$y_{O2}^{sp} = d,\ y_{23}^{sp} = r_{O2}y_{O2}^{sp} = r_{O2}d,\ y_{3D}^{sp} = r_{23}y_{23}^{sp} = r_{23}r_{O2}d,\ h^{sp} = r_{3D}y_{3D}^{sp} = r_{3D}r_{23}r_{O2}d. \quad (2)$$

3.2.3. Mathematical Program. The proposed linear integer program is formulated as follows. The notation used in the mathematical program can be found in the nomenclature.

The proposed model aims to find a configuration that secures the highest reachability for all possible scenarios. Meanwhile, the reachability of the paths in the scenarios

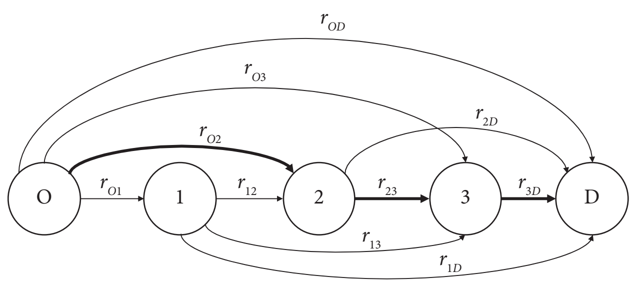

Figure 5: Reachability values and the selected links for path p in Figure 3(b).

is also maximized. Therefore, the objective is to maximize both path coverage and overall demand coverage. Specifically, the model seeks to maximize the sum of

- the minimum ratio of covered annual path demand across all scenarios (λ_1) and
- the minimum ratio of the total covered annual demand across all scenarios (λ_2).

$$\text{Max}\, Z = \lambda_1 + \lambda_2. \tag{3}$$

The variables λ_1 and λ_2 are determined through the following constraints:

$$\frac{h^{sp}}{d^{sp}} \geq \lambda_1, \quad p \in P,\, s \in S, \tag{4}$$

$$\frac{\sum_p h^{sp}}{\sum_p d^{sp}} \geq \lambda_2 \quad s \in S. \tag{5}$$

The problem is modeled as a flow problem, where demand flows from path origins to destinations through potential charging stations. Flow constraints are introduced to ensure the correct flow of demand across the network.

3.2.3.1. Origin Nodes

$$\sum_{j|b_{ij}^p=1} y_{ij}^{sp} = d^{sp}, \quad p \in P,\, i|o_i^p = 1,\, s \in S. \tag{6}$$

3.2.3.2. Destination Nodes

$$\sum_{i|b_{ij}^p=1} r_{ij} y_{ij}^{sp} = h^{sp}, \quad p \in P,\, j\,|u_j^p = 1, s \in S. \tag{7}$$

3.2.3.3. Intermediate Nodes (Candidate Charging Locations)

$$\sum_{j|b_{ij}^p=1} y_{ij}^{sp} = \sum_{j|b_{ji}^p=1} r_{ji} y_{ji}^{sp}, \quad p \in P, i|o_i^p = 0 \,\text{and}\, u_i^p = 0,\, s \in S. \tag{8}$$

Here, incoming flows are multiplied by the reachability coefficients r_{ji} to account for the number of vehicles that can traverse arc (i, j) without depleting their battery.

3.2.3.4. Capacity Constraints. The capacity of each charging station depends on the number of chargers installed. The annual capacity of a single charger is denoted by parameter C, representing the number of vehicles it can serve per year.

$$\sum_{p\in P} \sum_{j|b_{ij}^p=1} y_{ij}^{sp} \leq C x_i \quad i \in I,\, s \in S. \tag{9}$$

The total number of chargers in the system is restricted as follows:

$$\sum_{i\in I} x_i \leq n^{\text{tot}}. \tag{10}$$

Additionally, the maximum number of chargers and minimum number of chargers allowed at each station are given by

$$x_i \leq n^{\max} z_i, \quad i \in I, \tag{11}$$

$$x_i \geq n^{\min} z_i, \quad i \in I. \tag{12}$$

3.2.3.5. Variable Domains. Finally, sign restrictions and integrality constraints are

$$\begin{aligned} &x_i \geq 0 \,\text{and integer}, \quad i \in I, \\ &z_i \in \{0, 1\}, \quad i \in I, \\ &y_{ij}^{sp}, h^{sp} \geq 0, \quad p \in P, i \in O \cup I,\ j \in I \cup D, s \in S. \end{aligned} \tag{13}$$

4. A Case Study of Türkiye: Bursa–İzmir Region

The proposed methodology is applied to the last part of the İstanbul–İzmir motorway (coded as O5). O5 includes three parts, namely, the Gebze–Bursa toll motorway, the Bursa free beltway, and the Bursa–İzmir toll motorway. The first part is a route of 64 km, with seven exits and five service areas. The second part is a route of 35 km, with one exit and one service area. The last part is a route of 274 km, with 13 exits and nine service areas. The last part of O5 (Bursa–İzmir motorway) was selected for the case study since it is the longest uninterrupted route and has the highest number of exits and service areas.

4.1. Demand Forecasting for EVs. As explained in Section 3.1, the projected annual demand for EV on the selected route (Bursa–İzmir motorway) should initially be obtained to provide the inputs to the main mathematical model proposed in this study. As the first step of the hybrid demand forecasting phase, alternative scenarios are generated to cope with the critical level of uncertainty related to the variables that define the system. That is why a morphological scenario creation phase is followed as the first step of the methodology. At the beginning of the study, three candidate variables (income level, motorway toll charge rate, and vehicle ownership rate) are investigated. Due to the high correlation between the income level and vehicle ownership rate variables, "vehicle ownership rate" has been eliminated to ensure the internal consistency of the scenario options. Three different levels are introduced for each variable, and nine future pictures are derived based on two variables

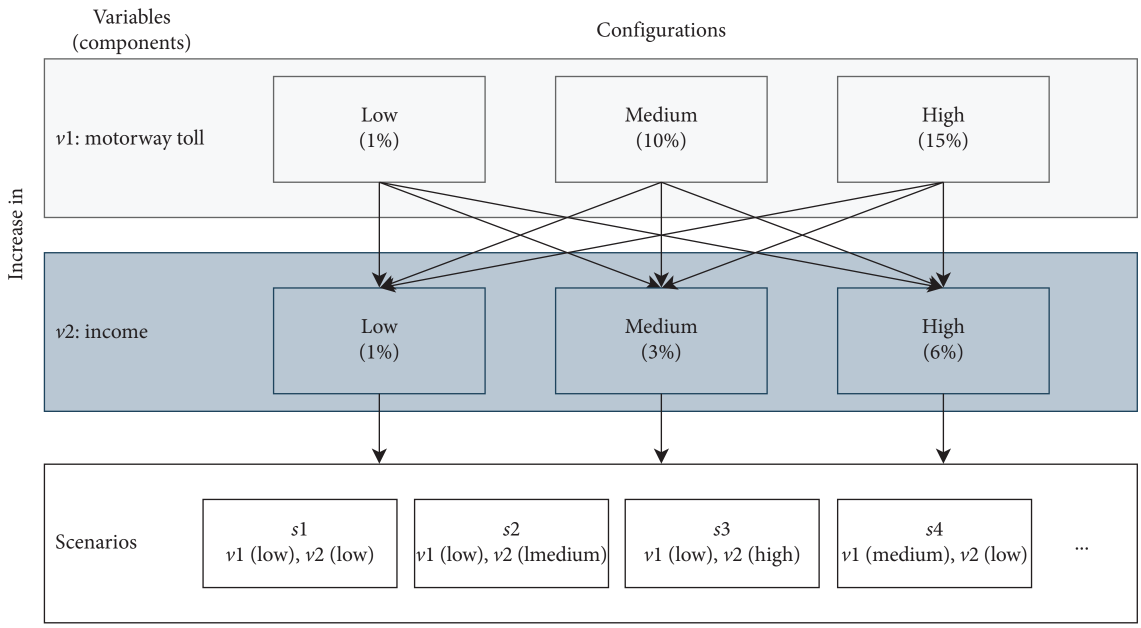

Figure 6: Constructing scenarios through morphological analysis.

(motorway toll charge and income), and three different configurations (low, medium, and high), as given in Figure 6. The degree of configurations was selected considering the historical macroeconomic factors (e.g., GDP, inflation).

After generating these scenarios, a gravity model estimates the "increase in the number of vehicles using the Bursa–İzmir motorway." Although the standard form of the gravity model estimates the flow between two points based on their populations, economic sizes, and distance between them, this study develops a gravity model to calculate the total number of cars passing through the Bursa–İzmir motorway.

The gravity model is a straightforward method for estimating intercity traffic loads, using city populations and the distance between cities as key explanatory variables. Despite its simplicity, the model remains a fundamental tool in transportation planning and urban economics because of its significant advantages and intuitive logic.

Among its key explanatory variables, population plays a central role. Larger cities naturally generate more trips because city populations are closely linked to factors such as the number of jobs, GDP, trade volume, retail space, and tourist attractions like hotels and museums. As a result, the population serves as an effective proxy for these related economic and social dimensions.

Distance is another critical factor in the model, reflecting the well-known "distance decay" effect: As travel time, costs, or physical separation between cities increase, travel demand typically declines. While physical distance offers a basic measure, variables such as travel time, generalized cost (which combines travel time, tolls, and fares), and perceived travel comfort provide more accurate representations of the deterrent effect of distance on travel behavior. The complete list of variables used in the gravity model is given in Table 2.

Data for the model can be readily obtained and typically contain less noise, making it highly suitable for empirical analysis. The parameters can be calibrated using traffic count data from a sample of routes through appropriate econometric methods. This calibration process ensures that the model reflects the specific travel behavior of a given region, thereby enhancing its accuracy and reliability.

One of the key advantages of the model is its ability to predict the impact of demographic or economic changes on traffic patterns. For instance, if City A's population is projected to grow by 20% over the next 2 decades, the new population figure can be incorporated into the model to estimate the resulting increase in traffic to other cities. This predictive capability provides valuable insights for long-term transportation planning and infrastructure development.

Moreover, the model goes beyond estimating traffic on individual routes; it calculates traffic flows between every pair of cities within the study area simultaneously. The result is an O–D matrix, a critical input for identifying optimal locations for new logistics hubs, freight terminals, and other transportation facilities.

Despite its relatively simple structure, the model has been validated across numerous studies and real-world applications. It consistently produces results that align closely with observed traffic patterns, particularly for larger intercity flows where aggregate behavior minimizes individual variations. As such, it offers a practical balance between simplicity and accuracy.

However, it is important to recognize the model's limitations. Oversimplification is a major concern, as the model does not account for individual traveler preferences, trip purposes, or socioeconomic differences; for example, business travelers may be less sensitive to cost than leisure

Table 2: Variables used in the gravity model.

Variable	Definition	Data source
x_1: number of cars passed through	The number of cars that passed through the selected path in 2019	GDH
x_2: toll	The 2020 toll charge for the selected path	GDH
x_3: route length	The length of the selected path	GM
x_4: average length of alternative routes	The average length of the alternative routes between origin and destination points of the selected path	GM
x_5: population of entry POIs	Total population of the POIs around the origin of the selected path.	TSI
x_6: population of exit POIs	Total population of the POIs around the destination of the selected path.	TSI
x_7: number of cars at entry POIs	Total number of vehicles at the POIs around the origin of the selected path.	TSI
x_8: number of cars at exit POIs	Total number of vehicles at the POIs around the destination of the selected path.	TSI
x_9: income of entry POIs	Total gross domestic product of the POIs around the origin of the selected path.	TSI
x_{10}: income of exit POIs	Total gross domestic product of the POIs around the destination of the selected path.	TSI

Abbreviations: GDH, General Directorate of Highways; GM, Google Maps; TSI, Turkish Statistical Institute.

travelers. Additionally, network effects are overlooked: The basic model assumes traffic occurs along isolated routes and does not consider the broader network structure. As a result, it may overestimate traffic on slower, congested routes and underestimate flows on faster, parallel alternatives.

The parameters of Equation (14), which utilizes all the descriptive variables, are estimated. In this equation, nonlinearity is considered by taking the logarithms of each variable, and the coefficients are obtained as flexibilities.

$$\ln x_1 = b_0 + \sum_{i=1}^{9} b_i \times \ln\ x_{i+1} + e. \tag{14}$$

The equation is estimated by using ordinary least squares (OLS), and Huber–White–Hinkley heteroskedasticity consistent standard errors and covariance are used. The estimation results are presented in the Appendix (see Tables A1 and A2). Even though the R^2 value of Equation (14) is 63%, almost half of the explanatory variables do not have the expected signs, while the other half is not meaningful, with an error margin of 5%. The main reason for this situation is the multicollinearity problem (the correlation coefficients between the number of cars at the entry points of interest (POIs) and the population of exit POIs, between the number of cars at exit POIs and the number of cars at entry POIs, and among toll for 2020, route length, and the average length of alternative routes are approximately 0.99).

According to the results given in Appendix Table A1, the coefficients of the variables are almost the same magnitude with opposite signs. A hypothesis test is conducted to validate this observation. The hypothesis test does not reject the null hypothesis of equal and opposite signs of these coefficients ($F = 1.62$; Prob. > 0.10). To resolve the multicollinearity problem between the number of vehicles and population without discarding any variables from the model, a new variable is produced: The number of vehicles per person for both entry and exit POIs. The ratio of the number of cars at entry POIs to the population of entry POIs and the ratio of the number of cars at exit POIs to the population of exit POIs are calculated and used for estimations. The estimation results are presented in Appendix Table A2.

According to the results given in Appendix Table A2, the signs of the coefficients are as expected. However, the coefficients of some variables are very close. When coefficient equalities are tested, the null hypothesis of close magnitude is not rejected ($F = 1.47$; Prob. > 0.10), and these variables are brought together.

The results of the final equation are presented in Table 3. In this situation, all variables have the expected signs and are significantly estimated. With these corrections, R^2 is sustained at the level of equation (14). A 1% increase in the number of vehicles per capita results in a 7.8% increase in the number of trips, while a 1% increase in per capita income results in an increase of 7.1%. When the toll charge is increased by 1%, the number of trips is reduced by 2.3%. When the length of the alternative route increases by 1%, the number of vehicles passing through the motorway increases by 1.9%. All diagnostic checks, such as heteroscedasticity, normality of residuals, and nonlinearity, for the final equation estimation are run, and no significant problem is observed.

This result shows that the effect of descriptive variables at both ends of the route is the same. For the route A.B., $A = 10, B = 50$ generates the same traffic as $A = 50, B = 10$. When the error terms of the final gravity model are investigated, it can be observed that the errors for the "Bursa Batı" entry and exit are higher. This is due to the addition of the population of Istanbul and the corresponding correction.

The gravity model is run nine times to calculate the total number of cars passing through the Bursa–İzmir motorway for each scenario created in the first step. As a result, nine values have been calculated (107%, 133%, 148%, 95%, 145%, 183%, 72%, 110%, and 171%).

As the last step, another morphological scenario analysis was conducted. For each of the projected traffic flow scenarios, three different EV share values (1%, 2%, and 5%) are incorporated to cover alternative futures for different electrification rates of vehicles.

4.2. Recommended EV Charging Station Locations. The proposed mathematical model is applied to the Bursa–İzmir motorway (Figure 7), where the network has 12 O–D points

Table 3: Estimation results of the final gravity model.

EQ3. Dependent variable: Ln (number of cars passed through)				
Method: least squares	**Included observations: 132**			
Variable	**Coefficient**	**Std. error**	***t*-statistic**	**Prob.**
C	−92.6625	18.1574	−5.1033	0.0000
ln (number of cars at entry POIs/population of entry POIs) + ln (number of cars at exit POIs/population of exit POIs)	7.7937	1.7943	4.3436	0.0001
ln (income of entry POIs) + ln (income of exit POIs)	7.0753	1.0612	6.6673	0.0000
ln (average length of alternative routes)	1.8925	0.4180	4.5278	0.0000
ln (toll)	−2.2963	0.4589	−5.0041	0.0000
DUM	−2.4714	0.8415	−2.9367	0.0046
R-squared	0.6258	Mean dependent var		8.5585
Adjusted *R*-squared	0.6110	SD dependent var		1.8459
SE of regression	1.1514	Akaike info criterion		3.1642
Sum of squared residuals	167.0349	Schwarz criterion		3.2952
Log likelihood	−202.8364	Hannan–Quinn crit.		3.2174
Durbin–Watson stat	1.0821	Wald *F*-statistic		26.0423
Prob (Wald *F*-statistic)	0.0000			

and 66 paths. The nine service areas ($S_1, S_2, \ldots, S_9$) (Figure 7) on the motorway are determined as the candidate points for the charging stations. Based on the O–D points and the candidate points, the expanded network is derived from 21 points and 253 arcs. The lengths of the arcs are measured based on the real road map. The gravity model provides the annual demand of the paths for the scenarios.

One important input of the model is the reachability values calculated for each arc using $r_{ij} = P\{R_{ij} > l_{ij}\}$. The gamma distribution is used for the driving range due to its flexibility [61, 62]. It is assumed that R_{ij} has a gamma distribution with shape parameter $\kappa = 50$ and scale parameter $\theta = 5$ if $i \in I$ and has a gamma distribution with shape parameter $\kappa = 20$ and scale parameter $\theta = 6.25$ if $i \in O$. This implies that $E[R_{ij}] = 250$, $\mathrm{Var}(R_{ij}) = 1250$, and $\mathrm{CV}(R_{ij}) = 0.14$ if $i \in I$; $E[R_{ij}] = 125$, $\mathrm{Var}(R_{ij}) = 781.25$, and $\mathrm{CV}(R_{ij}) = 0.22$ if $i \in O$. Thus, for the links through which the vehicles enter the motorway, the expected range is smaller, and the coefficient of variation of the range is larger than the one for the inner links of the motorway. Thus, it is assumed that most vehicles do not have a full battery when entering the motorway, and the uncertainty related to their battery levels will increase the variability of their ranges. This assumption is believed to be more realistic than assuming that all vehicles will have full batteries when entering the motorway.

The Parameter C, which represents the annual capacity of a charger defined as the number of cars that can be charged in a charger annually, is estimated based on the following assumptions: A car will be charged in 0.5 h, and at most 20% of the capacity is utilized. The value of 20% is derived from the observation that the current usage of the chargers is at most 20% in a day. The estimated parameters are presented in Table 4.

There are only a few electric charging stations in the service areas of the Bursa–İzmir motorway. The following information is revealed by the company's managers which owns the current charging stations. According to their

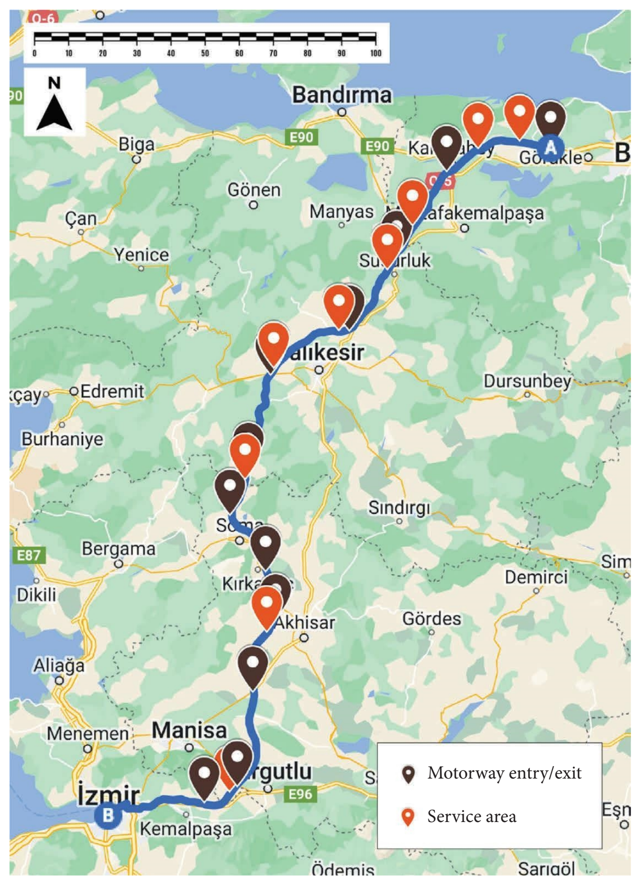

Figure 7: Map of the complete route from Bursa to Izmir.

feasibility analysis, the minimum and maximum allowed numbers of chargers in a station are set to 2 and 10, respectively. The total number of chargers allowed on the motorway will be 30 in their first investment plan.

The mixed-integer programming (MIP) model is solved with GAMS software with CPLEX solver on a laptop with a 12th Gen Intel Core i7-1255U processor, 1700 MHz with 32 GB RAM. Computation time is around 1 s for each run.

Table 4: Parameter estimations.

	Parameter	Value/source
l_{ij}	Length of arc (i, j)	Real roadmap data
d_s^p	The annual demand of path p under scenario s	Gravity model
r_{ij}	Reachability of arc (i, j)	For $i \in O \longrightarrow = 1 - \text{GAMMA.DIST}(l_{ij}/1.609, 20, 6.25, 1)$ For $i \in I \longrightarrow = 1 - \text{GAMMA.DIST}(l_{ij}/1.609, 50, 5, 1)$
C	Annual capacity of a charger (maximum number of cars that can be charged by the charger in a year)	$(24 \times 365/0.5) \times \%20 = 3504$
n^{min}	Minimum allowed number of chargers in a station	2
n^{max}	Maximum allowed number of chargers in a station	10
n^{tot}	The total allowed number of chargers built in the system	30

Table 5: Model results.

Stations	Number of built chargers	
	$n^{tot} = 30$	$n^{tot} = 45$
S_1	10	10
S_2	2	10
S_3	7	10
S_4	10	9
S_5	6	3
S_6	2	2
S_7	2	6
S_8	0	2
S_9	0	0

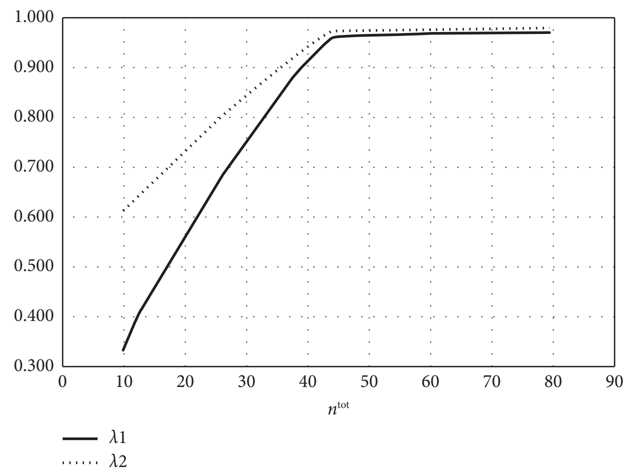

Figure 8: Reachability values for changing total number of chargers.

When the model is run using the given parameters, it is found that $\lambda_1 = 0.903$, $\lambda_2 = 0.935$. This means that with the resulting number of chargers at the stations, it is found that the reachability of any demand configuration (i.e., under any scenario) will be at least 0.935; and at the path level, the reachability will be 0.903 at minimum.

The number of chargers to be built at the stations is in the second column of Table 5. The model output recommends building the maximum number of charges at the first station and around the middle of the motorway. As the highest demand occurs at the path whose origin point is the start of the motorway (Bursa) and whose destination point is at the end of the motorway (Izmir), it is reasonable to build chargers at the first service area (S_1). This is also reasonable because the vehicles coming from outside the road network are assumed to have lower battery levels.

4.3. Sensitivity Analysis for Model Validation and Determination of the Ideal Number of Chargers. To validate the proposed model and determine the ideal number of chargers, a sensitivity analysis was conducted. The reachability or service level of the charging stations in the network is directly related to the total allowed number of chargers allowed in the system (n^{tot}). As n^{tot} increases, reachability represented by λ_1 and λ_2 is expected to improve.

In this analysis, the model was run for $n^{tot} = 10, 11, \ldots, 80$. The resulting values of λ_1 and λ_2 are presented in Figure 8. As expected, when $n^{tot} = 10$, values are relatively low ($\lambda_1 = 0.336, \lambda_2 = 0.616$). With higher values of n^{tot}, reachability increases almost linearly until approaching values close to 1. This finding supports the validity of the model, as it produces logical outcomes under the given conditions.

The same figure also provides clear insights into the optimal number of chargers. While reachability continues to rise as n^{tot} increases, the marginal improvement becomes negligible once values are close to 1. This threshold is reached at approximately $n^{tot} = 45$. Therefore, the ideal number of chargers for the Bursa–İzmir motorway is determined to be 45. At this level, the reachability values are $\lambda_1 = 0.967, \lambda_2 = 0.978$. The distribution of chargers across the stations is provided in the third column of Table 5.

5. Conclusions and Further Suggestions

This manuscript contributes significantly to understanding EV charging station issues, offering valuable insights for policymakers and researchers. It uses a methodology combining the gravity model, scenario analysis, and MILP. Applied to the Bursa–İzmir motorway, the model suggests optimal charger placements at seven out of nine service areas. A sensitivity analysis indicates that achieving a 97% reachability level requires 45 charging units.

However, certain limitations warrant acknowledgment. Firstly, the study's focus on the Bursa–İzmir motorway may limit the generalizability of findings to other regions. Data limitations, specifically the reliance on a single-year dataset, could affect the representation of long-term travel patterns. External factors, such as economic conditions, government policies, and cultural acceptance, are not explicitly considered, which impacts the study's holistic perspective. The research highlights the importance of incorporating broader geographical considerations, diverse datasets, and comprehensive sensitivity analyses in future studies.

While the present study primarily focuses on demand projections for EV charging infrastructure, it is essential to acknowledge that the power supply capacity of the regional grid plays a crucial role in determining the feasible scale of charging facilities. In many practical projects, limited power load capacity can restrict the number and type of charging stations that can be deployed.

While this study adopts an annual demand perspective suitable for strategic planning, future research could benefit from incorporating daily or hourly demand variations. Such an approach would allow for a more detailed analysis of peak load issues, potential charging congestion, and interactions with the power grid. Although determining the optimal number of chargers remains a strategic decision, introducing finer temporal granularity would provide valuable insights into the operational robustness of the charging network and its ability to maintain service levels under fluctuating demand conditions.

For the study area, we assume sufficient power supply capacity to meet the projected charging demand. This assumption is made due to the lack of detailed grid capacity data; however, future research should explicitly integrate power supply constraints into the modeling framework. This would enable a more comprehensive assessment, ensuring that both demand and infrastructure development plans are technically and economically feasible.

Nomenclature

Abbreviations

EV	Electric vehicle
FCLP	Flow capturing location problem
FRLP	Flow refueling location problem
ILP	Integer linear programming
IP	Integer programming
MCLP	Maximal coverage location problem
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear programming
MIP	Mixed-integer programming
MPRLM	Multipath refueling location model

Sets

O The set of origin points in N
D The set of destination points in N
I The set of candidate stations in N
P The set of possible paths
S The set of scenarios

Indices

$p \in P \quad (i, j) \in A'$ of network $G'(N, A')s \in S$

Parameters

l_{ij} Length of arc (i, j)
d^{sp} Annual demand of path p in scenario s
r_{ij} Reachability of arc (i, j); $r_{ij} = P\{R_{ij} > l_{ij}\}$
C Annual capacity of a charger (maximum number of cars that can be charged by a charger in a year)
$n^{\min}$ Minimum number of allowed chargers in a station
$n^{\max}$ Maximum number of allowed chargers in a station
n^{tot} Maximum number of allowed chargers in the entire system
b_{ij}^{p} Binary parameter indicating if arc (i, j) can be used in path p or not, i.e., $b_{ij}^{p} = \left\{\begin{array}{ll} 1 & \text{if } (i, j) \in A_p \\ 0 & \text{otherwise} \end{array}\right\}$
a_i^p Binary parameter indicating if point i is on path p or not, i.e., $a_i^p = \left\{\begin{array}{ll} 1 & \text{if } i \in N_p \\ 0 & \text{otherwise} \end{array}\right\}$
o_i^p Binary parameter indicating if point i is the origin of path p or not, i.e., $o_i^p = \left\{\begin{array}{ll} 1 & \text{if } i = o_p \\ 0 & \text{otherwise} \end{array}\right\}$
u_i^p Binary parameter indicating if point i is the destination of path p or not, i.e., $u_i^p = \left\{\begin{array}{ll} 1 & \text{if } i = d_p \\ 0 & \text{otherwise} \end{array}\right\}$

Decision Variables

x_i Integer variable representing the number of chargers built at station i, $i \in I$
z_i Binary variable indicating if any charger is built at station i, $i \in I$, or not, i.e., $z_i = \left\{\begin{array}{ll} 1 & \text{if } x_i > 0 \\ 0 & \text{otherwise} \end{array}\right\}$
y_{ij}^{sp} Expected number of cars using arc (i, j) on path p in scenario s
h^{sp} Expected covered annual demand of path p under scenario s
λ_1 Minimum ratio of the covered annual path demands in all scenarios
λ_2 Minimum ratio of the covered annual total demand in all scenarios

Appendix A

Table A1: Estimation results of the preliminary gravity model.

EQ1. Dependent variable: ln (number of cars passed through)				
Method: least squares		**Included observations: 132**		
Variable	**Coefficient**	**Std. error**	***t*-statistic**	**Prob.**
C	−27.6134	17.1981	−1.6056	0.1132
ln (toll)	−1.1201	0.9478	−1.1818	0.2416
ln (route length)	−0.7850	0.5734	−1.3691	0.1757
ln (average length of alternative routes)	1.3820	0.4422	3.1256	0.0027
ln (population of entry POIs)	−2.6619	1.7298	−1.5389	0.1287
ln (population of exit POIs)	−3.9180	1.8347	−2.1355	0.0365
ln (number of cars at entry POIs)	3.0027	1.6994	1.7669	0.0819
ln (number of cars at exit POIs)	4.1578	1.7877	2.3258	0.0232
ln (income of entry POIs)	2.0060	0.9062	2.2135	0.0304
ln (income of exit POIs)	2.6965	0.9343	2.8861	0.0053
R-squared	0.6293	Mean dependent var		8.5585
Adjusted R-squared	0.6020	SD dependent var		1.8459
SE of regression	1.1646	Akaike info criterion		3.2154
Sum of squared residuals	165.4644	Schwarz criterion		3.4337
Log-likelihood	−202.2128	Hannan–Quinn criterion		3.3041
Durbin–Watson stat	1.3183	Wald F-statistic		21.6584
Prob (Wald *F*-statistic)	0.0000			

Table A2: Estimation results of the revised gravity model.

EQ2. Dependent variable: Ln (number of cars passed through)				
Method: least squares		**Included observations: 132**		
Variable	**Coefficient**	**Std. error**	***t*-Statistic**	**Prob.**
C	−54.5280	11.3158	−4.8187	0.0000
ln (number of cars at entry POIs/population of entry POIs)	5.0266	1.5631	3.2158	0.0017
ln (number of cars at exit POIs/population of exit POIs)	5.3693	1.5631	3.4350	0.0008
ln (income of entry POIs)	4.4812	0.6439	6.9595	0.0000
ln (income of exit POIs)	4.4922	0.6439	6.9765	0.0000
ln (average length of alternative routes)	1.4975	0.4005	3.7395	0.0003
ln (toll)	−1.9540	0.3781	−5.1682	0.0000
R-squared	0.5679	Mean dependent var		8.5585
Adjusted *R*-squared	0.5472	SD dependent var		1.8459
SE of regression	1.2421	Akaike info criterion		3.3231
Sum of squared residuals	192.8605	Schwarz criterion		3.4760
Log-likelihood	−212.3248	Hannan–Quinn crit.		3.3852
F-statistic	27.3853	Durbin–Watson stat		1.1734
Prob (*F*-statistic)	0.0000			

Data Availability Statement

The data supporting this study's findings are confidential.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Bora Cekyay: formal analysis, methodology, writing–original draft.

Özgür Kabak: formal analysis, methodology, software, writing–original draft.

Ozay Ozaydin: data curation, formal analysis, software, visualization, writing–original draft, writing–review and editing.

Mine Isik: data curation, formal analysis, writing–original draft.

Peral Toktas-Palut: formal analysis, writing–original draft.

Y. Ilker Topcu: data curation, formal analysis, writing–original draft.

Şule Onsel-Ekici: conceptualization, formal analysis, methodology, writing–original draft.

Burç Ulengin: conceptualization, formal analysis, methodology, writing–original draft.

Fusun Ulengin: conceptualization, formal analysis, methodology, supervision, writing–original draft, writing–review and editing.

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