Sustainable Planning of Electric Vehicle Charging Stations

A Bi-Level Optimization Framework for Reducing Vehicular Emissions in Urban Road Networks

E. Seilabi, Sania; Pourgholamali, Mohammadhosein; Miralinaghi, Mohammad; Homem de Almeida Correia, Gonçalo; Li, Zongzhi; Labi, Samuel

DOI
10.3390/su17010001

Publication date
2025

Document Version
Final published version

Published in
Sustainability (Switzerland)

sustainability

Article

Sustainable Planning of Electric Vehicle Charging Stations: A Bi-Level Optimization Framework for Reducing Vehicular Emissions in Urban Road Networks

Sania E. Seilabi [1], Mohammadhosein Pourgholamali [2], Mohammad Miralinaghi [3,*], Gonçalo Homem de Almeida Correia [4], Zongzhi Li [3] and Samuel Labi [2]

1 Department of Civil and Structural Engineering, State University of New York, University at Buffalo, Buffalo, NY 14260, USA; sesmaei@purdue.edu
2 Lyles School of Civil and Construction Engineering, Center for Connected and Automated Transportation, Purdue University, West Lafayette, IN 47907, USA; mpourgho@purdue.edu (M.P.); labi@purdue.edu (S.L.)
3 Department of Civil, Architectural, and Environmental Engineering, Illinois Institute of Technology, Chicago, IL 60616, USA; lizz@iit.edu
4 Department of Transport & Planning, Delft University of Technology, 2600 GA Delft, The Netherlands; g.correia@tudelft.nl
* Correspondence: smiralinaghi@iit.edu; Tel.: +1-(205)-861-7849

Abstract: This paper proposes a decision-making framework for a multiple-period planning of electric vehicle (EV) charging station development. In this proposed framework, transportation planners seek to implement a phased provision of electric charging stations as well as repurposing gas stations at selected locations. The developed framework is presented as a bi-level optimization problem that determines the optimal electric charging network design while capturing the practical constraints and travelers' decisions. The upper level minimizes overall vehicle CO emissions by selecting optimal charging stations and their capacities, while the lower-level models travelers' choices of vehicle class (EV or conventional) and travel routes. A genetic algorithm is developed to solve this problem. The results of the numerical experiments describe the sensitive nature of EV market penetration rates in the urban traffic stream and overall vehicle CO emissions to EV charging station availability and capacity. The findings can assist transportation agencies in designing effective EV charging infrastructure by identifying optimal locations and capacities, as well as in creating policies to encourage EV use over time. This study supports broader efforts to reduce air pollution and promote sustainable transportation by promoting EV adoption in the long term.

Keywords: electric vehicles; electric charging stations; air pollution reduction; sustainable transportation; facility location problem

Academic Editors: Damir Jakus and Josip Vasilj

Received: 19 November 2024
Revised: 13 December 2024
Accepted: 18 December 2024
Published: 24 December 2024

Citation: E. Seilabi, S.; Pourgholamali, M.; Miralinaghi, M.; Homem de Almeida Correia, G.; Li, Z.; Labi, S. Sustainable Planning of Electric Vehicle Charging Stations: A Bi-Level Optimization Framework for Reducing Vehicular Emissions in Urban Road Networks. *Sustainability* **2025**, *17*, 1. https://doi.org/10.3390/su17010001

1. Introduction

Greenhouse gas (GHG) is the main contributor to climate change. As a global effort to reduce GHG emissions, an international strategic long-term plan, called the 2017 Paris Agreement, was signed by 195 countries at the UN Climate Change Conference [1,2]. At present, the transportation sector heavily relies on internal combustion vehicles (ICVs) for passenger travel and goods shipments by highways and highway vehicle air emissions. According to [3–5], more than two-thirds of fossil fuels in the United States are consumed by the transportation sector. Transportation planners and engineers are therefore tasked with developing strategies and measures to cut back GHG emissions by ICVs. One of the consensuses reached by governments, organizations, and vehicle manufacturers around the globe is to gradually replace ICVs by introducing electric vehicles (EVs).

Essential to the success of this initiative is to promote technological advancements in manufacturing EVs and incentivize market share dominance in EV conservation and usage around the globe. In response to this initiative, automakers have invested billions of dollars to increase the production of EVs, which include battery electric vehicles (BEVs) or all-electric and plug-in hybrid electric vehicles (PHEVs). France and the U.K. have pledged to end ICV sales by 2040 to achieve the target emissions of the Paris Agreement [6]. EVs account for 12.1% of the total vehicles sold in EU markets in 2022 and around 20% of the new vehicle market in China [7,8]. Although the growth of the EV sales market is promising, the overall share of EVs is still comparatively low in the total vehicle sales market. This is particularly true in the U.S., even after implementing various EV-promotive programs. For instance, the Alternative Fuels Data Center (AFDC) and the 2022 U.S. Department of Transportation's Highway Statistics reveal that the U.S. EV market share still struggles to go above 2% [9,10]. The overall low adoption of EVs is due to several barriers, including high purchasing prices, the low driving range of a fully charged EV, and a scarcity of power replenishment infrastructure compared to ICVs. Another barrier to EV usage is the lack of enough charging infrastructure, as in the states of Indiana, Michigan, New York, and Texas [11–15]. There were just 56,000 public electric charging stations in the United States as of 2017, which, compared to the number of existing gas stations (which is reported at 115,000), is significantly low [16–18]. Because of the importance of electric charging infrastructures, the U.S. government granted a USD 5 billion budget for developing EV charging stations and infrastructure across the United States recently [19].

The development of charging stations helps to promote EVs and achieve the zero-emissions goal in the near future. Recent advancements in fast-charging technologies, coupled with improvements in battery storage capacity and the integration of Vehicle-to-Grid (V2G) systems, have accelerated the adoption of EVs globally [20–23]. These studies have explored the efficiency of charging station networks under these technologies and they discussed key benefits and limitations of electric vehicle charging technologies. However, despite these advancements, challenges in the widespread deployment of charging infrastructure in congested urban environments remain unresolved. As EVs dominate the automotive market and ICVs (and their refueling demand) decrease, gas stations will become economically less profitable. For example, recently, a gas station owner in Tahoma Park, Maryland, replaced the station's gas pumps with electric charging points [24]. This trend indicates that instead of purchasing a new right of way to install EV charging stations, investors can take advantage of the land areas currently occupied by existing gas stations. In this regard, if the existing gas station spaces are reused for EV charging stations, then major land acquisition investments could be avoided. At the ICV refueling stations, the existing gas pumps and new electric charging points can coexist until there is no demand for the pumps. At those points, the pumps would be removed.

Despite considerable progress in expanding EV infrastructure, the lack of adequate grid capacity to support widespread charging, uneven distribution of charging stations, and inefficiencies in managing demand during peak times continue to impede the seamless transition to EVs [25–28]. This paper addresses these challenges by presenting a long-term congestion-aware facility location model that optimizes both charging infrastructure placement and resource allocation. The presented decision-making framework can facilitate the infrastructure planning during the transition era, from ICVs to EVs. This supports the transport planner to develop and implement policies that promote sustainable and environmentally friendly transportation systems to reduce vehicular emissions. Specifically, a gradual transition and infrastructure preparation is needed by transport planners to make sure that travelers shift smoothly toward full adoption of EVs in a long-term horizon (for example, a 20-year planning horizon is aimed at France and the UK to achieve full adoption of EVs).

The remainder of this paper is structured as follows. The next section presents a literature review of the relative studies. Then, in Section 3, the problem statement and objectives of this paper are discussed. Section 4 introduces the preliminaries, and then the developed bi-level framework is presented. Section 5 discusses the solution algorithm. Next, the numerical results and discussion are presented, and some insights derived from numerical analyses and experiments are discussed. Lastly, some concluding remarks are provided.

2. Literature Review

The problem of facility locations in a traffic network has been widely investigated over the past decades. Some recent studies in the literature particularly focused on determining the optimal locations of EV charging stations (e.g., [29–31]) or alternative fuels such as hydrogen replenishing stations (e.g., [32–40]). Calandra et al. provide a thorough review of the management and challenges of hydrogen mobility [41]. The studies on electric charging station location problems can be divided into two main categories. The first category focuses on the electric charging station location problem, where the impacts of traffic congestion on the travelers' route choices are ignored and travel times of links are assumed to be constant (e.g., [28,42–46]). These studies can generally be considered more applicable for intercity trips. This is because in intercity trip contexts, route choices of travelers have a minimal impact on road network travel times. The next category, however, focuses on locating electric charging stations within metropolitan areas, taking into account the effects of traffic congestion on travelers' route choices (e.g., [30,47–50]). The studies that capture the travel time as a function of traffic flow are more appropriate for intracity trips, as traffic congestion is an important factor in travelers' route decision making. Table 1 presents a summary of the studies that captured the route choice behavior of travelers in their planning frameworks. As this paper considers traffic congestion, it falls into the second category. It should be noted, however, that the presented framework of this study can be applied to intercity trip applications. This can be achieved simply by removing the congestion effect and assuming that travel times are constant. This paper seeks to bridge the gap in the literature by incorporating a gradual transition toward fully electric charging infrastructure and removing the current gasoline stations. By considering congestion effects, the proposed framework provides a more realistic approach for planning urban EV infrastructure that can facilitate the gradual transition from internal combustion engine vehicles to EVs, ensuring long-term sustainability in urban transport systems.

Table 1. Electric charging station facility location studies that capture the route choice decision.

Reference	Charging Facility Type	Objective
[47]	Static charging	Minimizing EV users' station access cost with penalizing unmet demand
[48]	Wireless charging	Minimizing total system travel time
[49]	Static charging	Minimizing total system travel time and energy
[50]	Static, plug-in and dynamic wireless charging	Minimizing total system travel time and penalty fee for "failed" trips
[29]	Static charging	Maximizing the number of served EVs
[30]	Static charging	Minimizing the total infrastructure setup cost
[51]	Wireless charging	total cost of deploying all wireless charging stations in the network
[31]	Wireless charging	Maximizing the total outflow or total system travel time

Table 1. *Cont.*

Reference	Charging Facility Type	Objective
[28]	Static charging	Minimizing the unused charging capacity and travelers' costs
[52]	Static charging	Minimizing total service time
[53]	Static charging	Maximizing Distance coverage
[53]	Static charging	Maximizing Distance coverage
[54]	Static charging	Minimizing total cost
[55]	Static charging	Minimizing total cost
This study	Static charging	Minimizing vehicular emissions

3. Problem Statement, Objectives, Scope and Contribution

This study focuses on designing an optimal EV charging infrastructure network (including its locations and capacities) added to an existing urban roadway network. In this problem, the transportation planner seeks to determine an optimal network of EV charging stations over a multi-year planning period. For each planning phase, the best locations and capacities for constructing new charging stations are determined. In this regard, a bi-level optimization problem is developed. At the upper level, the planner aims to reduce total vehicle emissions by making decisions on the optimal capacities and locations of EV charging stations, forming the primary components of the new EV infrastructure network over the planning horizon. This network will involve converting selected refueling stations to electric charging stations, along with building electric charging stations at additional sites, with specific capacities assigned to each. The lower-level model captures the reactions of the travelers to the transport planners' decisions. More specifically, travelers aim to minimize their travel times by selecting travel paths and vehicle classes (EV or ICV) based on the established EV network from the upper-level decisions. EV travelers' route choice decisions are constrained by the limited driving range of EVs. Also, this study assumes that a certain proportion of ICVs needs to stop at a refueling station once to refuel during their trips. This portion of ICVs remains fixed within each planning period but varies across different periods within the overall planning horizon. At present, the driving ranges of EVs vary significantly by vehicle class and pre-trip charging level. In practice, partially charged EVs for long-distance commuting in large metropolitan areas are likely to visit fast-charging stations during the trips. Similar to some existing studies by [38,41,42], the current study also set the driving range of an EV to be lower than that of a fully charged EV. Further, the estimation of reductions in vehicle air emissions caused by EVs added to the traffic stream has not accounted for emissions from the power supply to the EV charging stations.

The contributions of this paper are threefold. The first is to incorporate EV choice into the traveler's route choice model for a given electric charging infrastructure network over a long-term planning horizon. The EV choice is made based on the gradual EV technological advancements that affect EV ownership costs and driving ranges over time. As a practical matter, the added costs of EVs relative to ICVs over time are considered to reduce. In consideration of differences in EV charging levels, varying driving ranges are considered for different classes of EVs over the planning horizon. The second is to consider a phased-transition plan from ICV use to full EV adoption over planning periods with a gradual replacement of the existing ICV gas stations by EV stations. The third is to introduce the objective of minimizing vehicular air emissions in conjunction with minimizing travelers' travel times in the route choice model to develop an optimal plan for deploying the EV charging infrastructure network composed of EV charging stations converted from the existing ICV gas stations and built at prioritized new locations over a planning horizon.

4. Methodology

4.1. Preliminaries

This subsection introduces the notations and the background of the developed mathematical model in this study. Let $G = (N, A)$ represent the roadway network, and N and A denote the nodes and the links within the network, respectively. The sets of origins and origin–destination (O-D) pairs are identified as S and W, respectively. Here, s and r indicate the origin and destination for O-D pair w, respectively. The multiple-period planning horizon is segmented into T periods, each encompassing multiple years. This study considers two vehicle classes, EVs and ICVs. ICVEs are further divided into two subcategories with respect to their refueling requirements. The user classes are shown by M and include three classifications. (1) Class 1 represents ICVs that do not require refueling ($m = 1$); (2) Class 2 denotes ICVs that need to refuel during their trips ($m = 2$); and (3) Class 3 signifies EVs that need to recharge if needed ($m = 3$). Additionally, the nodes in N are divided into three subsets. (i) $\hat{N}$ includes potential locations for new electric charging station construction; (ii) $\overline{N}$ consists of nodes that have operating refueling stations; and (iii) the remaining nodes are represented by $\overline{\overline{N}}$. This research treats nodes with available refueling stations as potential sites for electric charging stations ($\overline{N} \subseteq \hat{N}$), each having a fixed flow capacity denoted by f_i^t. As a result, these nodes can serve both ICVs and EVs. Let $\nu_{ij}^{w,t,m}$ represent the traffic flow of user class m traveling between O-D pair w, while ν_{ij}^t denotes the total traffic flow on link (i, j) during period t. The travel time for link (i, j) is denoted as σ_{ij}^t. This study follows the Bureau of Public Roads (BPR) link performance function to consider the impact of traffic flow on link travel time. The link travel times are presented as follows:

$$\sigma_{ij}^t = \theta_{ij}^t \left(1 + 0.15 \left(\frac{\nu_{ij}^t}{\chi_{ij}^t} \right)^4 \right) \quad \forall (i, j) \in A, \forall t \tag{1}$$

where χ_{ij}^t and θ_{ij}^t represent the capacity of link (i, j) and the base free-flow travel time and during period t, respectively. A summary of notations used in this research can be found in Table 2.

Table 2. Summary of notations.

Sets	
N	Set of nodes
A	Set of links
O	Set of origins
W	Set of O-D pairs
M	Set of user classes (EV, ICV)
$\hat{N}$	Set of candidate locations for new electric charging station construction
$\overline{N}$	Set of nodes with operating refueling stations
$\overline{\overline{N}}$	
Parameters	
χ_{ij}^t	Capacity of link (i, j) during period t
B^t	EV charging station construction budget during period t
R^t	EV driving range during period t
η	value of time for travelers
θ_{ij}^t	Base free-flow travel time of link (i, j) during period t
d^{t^*}	Potential EV market size for period t
Variables	
$\nu_{ij}^{w,t,m}$	Flow for user class m of O-D pair w during period t

Table 2. *Cont.*

Sets	
v_{ij}^{t}	Total traffic flow on link (i,j) during period t
$d^{w,t,m}$	Travel demand of O-D pair w during period t of user class m
σ_{ij}^{t}	Travel time for link (i,j) during period t
$y_{i}^{k,t}$	Binary variable that indicates charging infrastructure investment in each period
$e_{ij}^{w,t,2}$	Binary variable that indicates if link (i,j) is part of the feasible subnetwork of ICVs traveling from origin $s$in period t.

Figure 1 illustrates the structure of the bi-level problem. In the upper level (detailed in Section 4.2), transportation planners collaborate with private-sector investors to determine the optimal sites and operational capacities for EV charging stations within the roadway network, aiming to minimize vehicle CO emissions. The deployment of EV charging stations is planned through a smooth conversion of existing gas stations, along with the construction of new charging stations at prioritized locations. These decisions must adhere to the budget constraints set for each planning period. This study assumes that the operational capacities of both ICV refueling stations and electric charging stations are adequate to meet the operational needs of travelers. At the lower level (explored in Section 4.3), travelers seek to choose their vehicle classes (EVs, which incur purchasing costs, and ICVs, which may or may not require refueling) and routes that minimize the travel times for O-D paths, in accordance with the user equilibrium principle. The models for the lower and upper levels are executed iteratively, continuing until they fulfill the termination criteria established for both models.

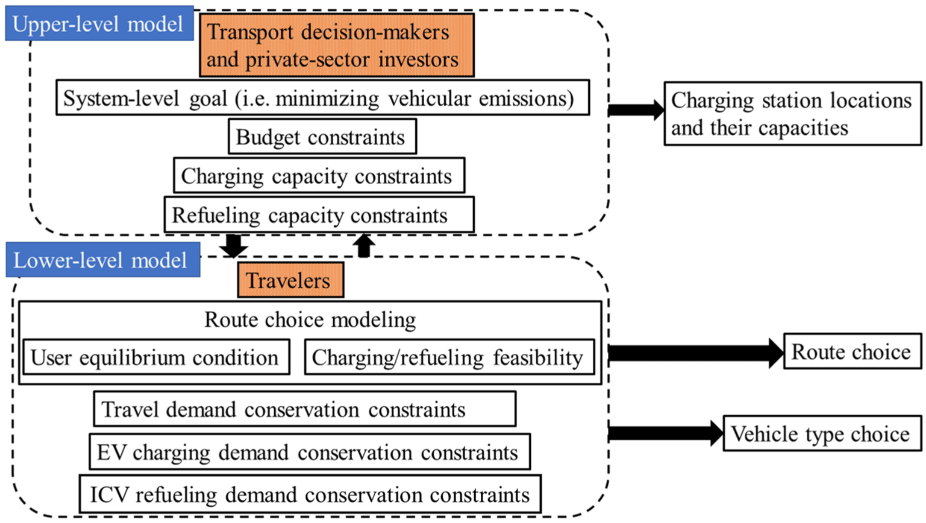

Figure 1. The bi-level structure of the developed framework.

4.2. Upper-Level Model

In this subsection, the developed upper-level optimization model is presented. As presented in the previous subsection, the upper-level problem captures the decisions of the transport planners and private sector investors. The upper-level model has the following specifications:

$$\min_{\varphi,y,\zeta,\beta} Z^{U} = \sum_{t} \sum_{(i,j)\in A} \sum_{m<3} v_{ij}^{w,t,m} Y_{ij}^{t}\left(v_{ij}^{t}\right) \tag{2}$$

$$Y_{ij}^{t}\left(\nu_{ij}^{t}\right) = 0.2038\sigma_{ij}^{t}\left(\nu_{ij}^{t}\right)\cdot\exp\left(\frac{0.7962L_{ij}^{t}}{\sigma_{ij}^{t}\left(\nu_{ij}^{t}\right)}\right) \quad \forall(i,j)\in A,\forall \tag{3}$$

$$\sum_{(i,k)} c_i^{k,1} y_i^{k,1} \leq B^1 \tag{4}$$

$$\sum_{(i,k)} c_i^{k,t}\cdot\left(y_i^{k,t} - y_i^{k,t-1}\right) \leq B^t \quad \forall t>1 \tag{5}$$

$$\varphi_i^t \leq M\cdot\zeta_i^{t,2} \quad \forall t,\forall i\in\overline{N} \tag{6}$$

$$\varphi_i^1 = 1 \quad \forall i\in\overline{N} \tag{7}$$

$$\varphi_i^t \leq \varphi_i^{t-1} \quad \forall t,\forall i\in\overline{N} \tag{8}$$

$$\beta_i^{k,t} \leq \left(p_i^k - p_i^{k-1}\right)\cdot y_i^{k,t} \quad \forall t,\forall k,\forall i\in\hat{N} \tag{9}$$

$$\sum_k \beta_i^{k,t} = \zeta_i^{t,3} \quad \forall t,\forall i\in\hat{N} \tag{10}$$

$$y_i^{k,t-1} \leq y_i^{k,t} \quad \forall t,\forall k>1,\forall i\in\hat{N} \tag{11}$$

$$y_i^{k,t},\varphi_i^t \in \{0,1\} \quad \forall t,\ \forall i,\ \forall k,\ \forall(i,j)\in A \tag{12}$$

$$\zeta_i^{t,m},\beta_i^{k,t} \geq 0 \quad \forall m,\ \forall k,\forall t,\forall i \tag{13}$$

Equation (2) represents the upper-level model's objective function. The objective function minimizes the total vehicular emissions caused by ICVs over the planning horizon. Equation (3) calculates the CO emissions of ICVs on link (i,j) in period t. This paper only uses CO as a vehicular emissions indicator, as it is shown that ICVs are the primary source of both CO and other similar pollutant emissions [56]. Many studies in the literature used this function to determine the vehicular emissions (e.g., [57–59]). As this study assumes the construction budget is limited, Constraints (4) and (5) ensure that the construction cost is held under the available budget at each period. Specifically, Constraints (4) and (5) focus on the construction budget at period 1 and any other period t, respectively. Constraint (5) states that, if in period $(t-1)$, an electric charging station of operation level k does not exist at node i ($y_i^{k,t} = 0$), an investmen of c_i^k is needed in the next period, period t, for the charging station construction. However, if in period $(t-1)$, an electric charging station at node i exists ($y_i^{k,t} = 1$), then the construction cost is zero. Constraints (6) state that the refueling stations at node i are considered to be decommissioned in period t if no ICVs use that refueling station in that time period. Constraints (7) ensure that the initial existing refueling stations in the network operate and serve ICVs in the first period. If at any period $t-1$, a refueling station stops operating and serving ICVs, Constraints (8) ensure that the mentioned refueling station does not operate in the following planning periods either. Constraints (9) and (10) derive the electric charging stations' operating levels at any time period t. Next, Constraints (11) make sure that the operation level of an electric charging station at node i does not decline over the planning horizon. Equations (12) and (13) show the domains for the decision variables.

4.3. Lower-Level Model

This subsection presents the developed lower-level model of this study. The lower-level model of the developed framework captures the reactions of travelers to the transportation planners and private-sector investors' actions and policies. More specifically, the route choice behavior and vehicle class decisions of travelers are captured by the lower-level model. To capture the vehicle class choice behavior of travelers and, therefore, the adoption rate of EVs, this paper utilizes a diffusion model to predict the evolution of the travel demand of EVs ($d^{w,t,3}$, for any O-D pair w at period t). In line with the diffusion model, the EV market penetration rate in each time period t depends on both the prior period's adoption rate and the net benefit gained by EVs in the prior period. This diffusion model is commonly employed in previous studies to model the adoption rate of advanced vehicles such as hydrogen fuel vehicles [60] and automated vehicle technology [48,61]. Based on this model, this study formulates the EV adoption rate over planning period t as follows:

$$d^{w,t,3} = d^{w,t-1,3} + h^{w,t} \cdot \left(d^{w,t-1,3}\right) \cdot \left(1 - \frac{d^{w,t-1,3}}{d^{t^*}}\right) \quad \forall t, \forall w \tag{14}$$

where d^{t^*} represents the potential EV market size for period t, achievable under ideal conditions, such as the availability of multiple refueling stations and competitive vehicle pricing.

Let η denote the value of time for travelers, and this study assumes the value of time is constant throughout the planning periods. As the purchase cost of EVs is higher than ICVs, an extra cost is imposed on EV users per trip compared to ICVs. This imposed cost is denoted by x^t. Let $h^{w,t}$ represent the growth variable for any O-D pair w. $h^{w,t}$ is presented as follows:

$$h^{w,t} = \varsigma e^{\varpi \cdot \left(\eta\left(\pi_r^{w,t-1,2} - \pi_r^{w,t-1,3}\right) - x^{t-1}\right)} \quad \forall t, \forall w \tag{15}$$

where ς and ϖ represent the parameters of the diffusion model. Moreover, $\pi_r^{w,t-1,m}$ denotes the travel time of travelers that travel between O-D pair w in period $(t-1)$ and belong to class m. Therefore, $\eta\left(\pi_r^{w,t-1,2} - \pi_r^{w,t-1,3}\right) - x^{t-1}$ can be interpreted as the net benefit gained by EV travelers based on their travel time compared to the class of ICV travelers that refuels.

To take the limited driving range of EVs into route choice consideration, this paper extends the single-period constraints proposed by [49] to a multi-period context. This study assumes a linear function to calculate the EVs' electricity consumption based on travel distance. Also, in this paper, it is assumed that the limited driving range of EVs, denoted by R^t, increases over planning periods due to the expected technological advances. Let $u_i^{w,t}$ and $u'^{w,t}_i$ represent the distance that EVs of O-D pair w traveled since the latest recharging at an electric charging station at each time period t. Once an EV visits a charging station, $u'^{w,t}_i$ is set to zero. At each node i, $u_i^{w,t}$ does not exceed the driving range limit R^t. The feasible driving range of EVs at each period is formulated as follows:

$$u_j^{w,t} \geq u'^{w,t}_i + L_{ij}^t - M \cdot \left(1 - e_{ij}^{w,t,3}\right) \quad \forall (i,j) \in A, \forall w, \forall t \tag{16}$$

$$u_j^{w,t} \leq R^t \quad \forall t, \forall w, \forall j \tag{17}$$

$$u'^{w,t}_i \geq u_i^{w,t} - My_i^{1,t} \quad \forall t, \forall w, \forall i \in \hat{N} \tag{18}$$

$$u'^{w,t}_i \leq u_i^{w,t} + My_i^{1,t} \quad \forall t, \forall w, \forall i \in \hat{N} \tag{19}$$

$$u'^{w,t}_s = 0 \quad \forall s, \forall t, \forall w \tag{20}$$

$$u'^{w,t}_i \leq M \cdot \left(1 - y_i^{1,t}\right) \quad \forall t, \forall w, \forall i \in \hat{N} \tag{21}$$

$$-M\left(1 - u'^{w,t}_i\right) + \sum_{j:(j,i) \in A} \nu_{ji}^{w,t,3} \leq \phi_i^{w,t,3} \quad \forall t, \forall w, \forall i \in \hat{N} \tag{22}$$

$$M\left(1 - u'^{w,t}_i\right) + \sum_{j:(j,i) \in A} \nu_{ji}^{w,t,3} \geq \phi_i^{w,t,3} \quad \forall t, \forall s, \forall i \in \hat{N} \tag{23}$$

$$\phi_i^{w,t,3} \leq M \cdot y_i^{1,t} \quad \forall i, \forall w, \forall t \tag{24}$$

$$\sum_w \phi_i^{w,t,3} = \zeta_i^{t,3} \quad \forall t, \forall i \in \hat{N} \tag{25}$$

$$\forall t, \forall i \in \hat{N} \quad \forall t, \forall w, \forall i \tag{26}$$

$$e_{ij}^{w,t,3} \in \{0,1\} \quad \forall w,\ \forall t, \forall (i,j) \in A \tag{27}$$

where M is a large positive constant, and $e_{ij}^{w,t,3}$ is a binary variable showing if link (i,j) lies on a feasible path for EVs of O-D pair w in time period t, based on the range constraint. Constraint (16) determines the distance that travelers from origin s have traveled since their most recent stop at a charging station. Constraint (17) verifies that this distance remains within the limited driving range during period t. Constraints (18) and (19) ensure that if a charging station exists at node i, then $u'^{w,t}_i = u_i^{w,t}$, and Constraints (21) reset $u'^{w,t}_i$ to zero, indicating that the travel distance is reset after stopping at charging station i. Constraint (20) ensures that the traveled distance is zero at the trip origin. Constraints (22)–(25) determine the total flow of ICVs originating from node s and refuel at the refueling station of node i in period t. For additional details, refer to [49].

Similar to what is discussed about the limited range of EVs and their route choice decisions to recharge during their trips, this study captures the refueling needs of class 2 of ICVs during their trips. In this regard, this study models the route choice of this class during intracity trips. In this context, this study assumes that a certain ratio of ICV travelers (who are called class 2) needs to make one stop at a refueling station during their trips. In this paper, the considered ratio is assumed to be predetermined and known. In practical applications, this ratio should be estimated based on available data. At a time period t, if ICVs of O-D pair w refuel at node i, then $\alpha_i^{w,t}$ is equal to 1. Let $\gamma_i^{w,t}$ denote the number of refueling stops of ICVs of O-D pair w until node i in period t. Let $\phi_i^{w,t,2}$ represent the total flow of ICVs of O-D pair w that stop at node i to refuel in period t. Based on the mentioned assumptions and introduced notations, the following represents the driving range feasibility of ICVs:

$$\gamma_j^{w,t} \geq \alpha_j^{w,t} + \gamma_i^{w,t} - M \cdot \left(1 - e_{ij}^{w,t,2}\right) \quad \forall t, \forall w, \forall (i,j) \in A \tag{28}$$

$$\gamma_j^{w,t} \leq \alpha_j^{w,t} + \gamma_i^{w,t} + M \cdot \left(1 - e_{ij}^{w,t,2}\right) \quad \forall t, \forall w, \forall (i,j) \in A \tag{29}$$

$$\gamma_s^{w,t} = 0 \quad \forall t, \forall w, \forall s \in \left(N - \overline{N}\right) \tag{30}$$

$$\gamma_s^{w,t} \leq 1 \quad \forall t, \forall w, \forall s \in \overline{N} \tag{31}$$

$$\gamma_r^{w,t} = 1 \quad \forall t, \forall w, \forall r \tag{32}$$

$$-M\left(1 - \alpha_i^{w,t}\right) + \sum_{j:(j,i) \in A} \nu_{ji}^{w,t,2} \leq \phi_i^{w,t,2} \quad \forall t, \forall w, \forall i \in \overline{N} \tag{33}$$

$$M\left(1 - \alpha_i^{w,t}\right) + \sum_{j:(j,i) \in A} \nu_{ji}^{w,t,2} \geq \phi_i^{w,t,2} \quad \forall t, \forall s, \forall i \in \overline{N} \tag{34}$$

$$\phi_i^{w,t,2} \leq M \cdot \alpha_i^{w,t} \quad \forall i, \forall w, \forall t \tag{35}$$

$$\sum_w \phi_i^{w,t,2} = \zeta_i^{t,2} \quad \forall t, \forall i \in \overline{N} \tag{36}$$

$$\alpha_i^{w,t} \leq \varphi_i^t \quad \forall t, \forall w, \forall i \in \overline{N} \tag{37}$$

$$\zeta_i^{t,2} + \zeta_i^{t,3} \leq f_i^t \quad \forall t, \forall i \in \overline{N} \tag{38}$$

$$\alpha_i^{w,t}, \gamma_i^{w,t}, e_{ij}^{w,t,2} \in \{0,1\} \quad \forall t, \forall w, \forall i,\ \forall (i,j) \in A \tag{39}$$

$$\phi_i^{w,t,2}, \zeta_i^{t,2} \geq 0 \quad \forall t, \forall w, \forall i \in \overline{N} \tag{40}$$

where $e_{ij}^{w,t,2}$ indicates whether link (i,j) is part of the feasible subnetwork of ICVs traveling from origin s in period t. Specifically, $e_{ij}^{w,t,2}$ equals 1 when link (i,j) is a part of a feasible subnetwork of the ICVs of O-D pair w. Otherwise, it is 0. Equations (28) and (29) determine the total number of stops made by ICVs of O-D pair w to refuel in period t. Constraint (30) ensures that $\gamma_s^{w,t}$, the total number of refueling stops for ICVs, is zero if the trip originates from a location without an operating refueling station in period t. Moreover, if a refueling station exists at the origin of O-D pair w (node s), Constraint (31) allows ICVs to refuel at their starting point in period t. Constraint (32) requires ICVs of O-D pair w to make at least one stop at refueling stations during their trips and before reaching their destination node r in period t. Next, Constraints (33)–(35) determine the total refueling flow for ICVs originating from node s at a station located at node i during period t. Constraint (36) determines the total refueling demand at a refueling station of node i in period t. Constraint (37) specifies that ICVs cannot stop at node i unless a refueling station is present there in period t. Finally, Constraint (38) ensures that the combined refueling and electric charging flows remain within the capacity limits of the station at node i in period t.

We now develop a multi-class traffic assignment model, which incorporates the upper-level decisions and actions made by the transportation planner and private-sector investors. This assignment accounts for the limited driving range of EVs and the refueling needs of ICVs. Thus, the user equilibrium condition is achieved through a feasible subnetwork defined by $e_{ij}^{w,t,m}$. The lower-level optimization problem is structured as follows:

$$\min Z^L = \sum_{(i,j)\in A} \int_0^{v_{ij}^t} \sigma_{ij}^t(\omega) d\omega \tag{41}$$

$$\sum_{(w,m)} v_{ij}^{w,t,m} = v_{ij}^t \quad \forall (i,j) \in A,\ \forall t \tag{42}$$

$$\sum_{j:(j,i)\in A} v_{ji}^{w,t,m} - \sum_{j:(i,j)\in A} v_{ij}^{w,t,m} = q_i^{w,t,m} \quad \forall m,\ \forall w, \forall i, \forall t \tag{43}$$

$$v_{ij}^{w,t,m} \leq M \cdot e_{ij}^{w,t,m} \quad \forall m > 1,\ \forall (i,j) \in A, \forall w, \forall t \tag{44}$$

$$v_{ij}^{w,t,m} \geq 0 \quad \forall (i,j) \in A, \forall w, \forall t, \forall m \tag{45}$$

where $q_i^{w,t,m}$ for any O-D pair w is determined as follows:

$$q_i^{w,t,m} = \begin{cases} -d^{w,t,m} & \text{if } i \text{ is the trip origin} \\ d^{w,t,m} & \text{if } i \text{ is the trip destination} \\ 0 & \text{otherwise} \end{cases} \quad \forall m,\ \forall i, \forall t \tag{46}$$

Models (41)–(45) represent the static traffic assignment model, with Constraint (44) specifying that user classes 2 and 3 are restricted to their corresponding feasible routes. To solve the developed lower-level problem, the first-order condition of Model (41)–(45) is formulated to replace the objective function (41). This reformulation helps develop a tractable optimization that can be solved by commercial optimization solvers.

5. Solution Algorithm

This section describes the developed solution algorithm to solve the proposed bi-level optimization problem. The formulated bi-level optimization problem is classified as a typical discrete network design problem (DNDP), which is of the nature of nondeterministic polynomial-time (NP) hard in that it takes polynomial time to verify a candidate solution with no guarantee of being the global solution [62]. To ensure computational efficiency, heuristic algorithms using support functions, branch-and-bound, and active-set techniques are often sought to derive near-optimal solutions [63]. In the current study, a Genetic Algorithm (GA) is developed to solve the upper-level program at near-optimality with high computational efficiency. The GA-based solution technique was first introduced by [64], which is inspired by natural selection and belongs to the larger class of evolutionary algorithms. Over the last three decades, it has been employed for solving a wide range of NP-hard problems, particularly mixed-integer nonlinear problems (MINLPs) and DNDP problems. Some notable studies can be found in [58,65–67]. Algorithm 1 shows the GA used in this study. First, the GA's parameters are initialized, and in step 2, a set of random solutions is generated (pop_1). Next, the solutions in pop_1 are evaluated, and the best solution is stored in X_{best} (step 4). In step 5, an iterative process starts. In steps 5.1 and 5.2, crossover and mutation operators are applied to pop_1 to generate new solutions (pop_2). Next, solutions in pop_2 are evaluated based on the objective function of the problem (step 5.3). The best solution of pop_2 is stored in X_{new} and the number of iterations without a better solution found (γ) is increased by 1. If X_{new} is better than X, X updates to X_{new} and γ is set to zero. Next, some solutions from pop_1 and pop_2 are selected through tournament and roulette wheel selection methods to generate new solutions in the next iteration (step 5.9). If the current solution is not improved after γ_{max} trials, the solution algorithm stops and returns the current best solution (X_{best}). The lower-level optimization problem is formulated as a typical UE-based traffic assignment model readily solvable by the Frank–Wolfe algorithm for optimality. Specifically, the solution algorithm proposed by [68] is adopted for the current study to derive a solution.

Algorithm 1. GA for solving the upper-level model.

1	***Initialization*** GA's parameters
2	$pop_1 \longleftarrow$ Random solution generation ()
3	$\Omega \leftarrow$ Evaluation (pop_1)
4	$X_{best} \longleftarrow \underset{pop1}{\text{argmin}}\Omega$
5	***While*** $\gamma < \gamma_{max}$
5.1	$pop_2 \leftarrow$ Crossover (pop_1)
5.2	$pop_2 \leftarrow$ Mutation (pop_2)
5.3	$\Omega \leftarrow$ Evaluation (pop_2)
5.4	$X_{new} \longleftarrow \underset{pop2}{\text{argmin}}\Omega$
5.5	$\gamma \longleftarrow \gamma + 1$
5.6	***If*** $\Omega_{X_{new}} < \Omega_{X_{best}}$:
5.7	$X_{best} \leftarrow X_{new}$
5.8	$\gamma \longleftarrow 0$
5.9	$pop_1 \leftarrow$ Roulette wheel ($pop_1 \cup pop_2$)
6	***Return*** X_{best}

6. Computational Experiment

6.1. Problem Setting

6.1.1. Roadway Network

For the computational experiments, this study applies the proposed EV charging infrastructure network design model on the Sioux Falls roadway network, initially introduced by [69]. The Sioux Falls roadway network contains 24 nodes and 76 links. As depicted in Figure 2, Nodes 4, 10, 12, 14, 18, 20 and 22 marked in yellow have ICV refueling stations, and their refueling stations are candidates to be converted to EV charging stations. Nodes 16 and 17, marked in red, are candidates for locating new EV charging stations. In the computational experiments, the driving range of EVs is limited to 12 miles, unless stated otherwise. This value is comparable with a value used in some experimental studies using roadway networks comparable to the Sioux Falls roadway network [49,70,71].

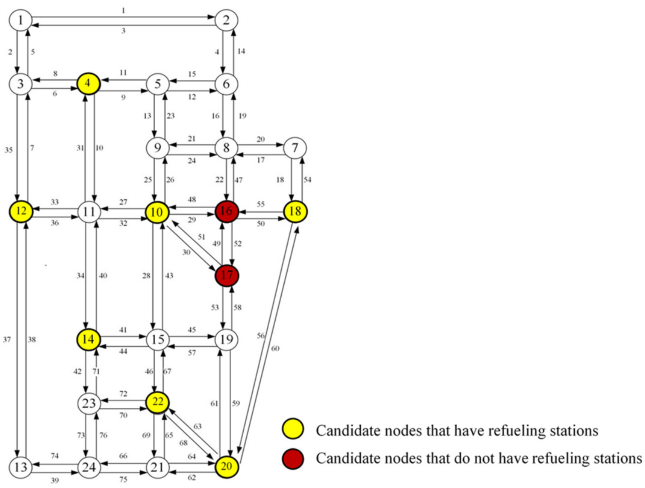

Figure 2. Schematic Sioux Falls roadway network and candidate nodes for new electric charging station construction.

6.1.2. Travel Demand Characteristics

On the travel demand side, 360,600 person-trips per hour are expected to utilize the network for a typical weekday in the first year. The planning horizon for deploying the EV charging infrastructure network is 20 years, which is divided into five periods. The annual growth rate of daily travel demand is 5% throughout the planning horizon.

6.1.3. EV Charging Station Capacities

Two operational levels are considered for each charging station: a first-level operation with a capacity of $p_i^1 = 300$ and a second-level operation with a capacity of $p_i^2 = 400$. The construction cost of a charging station depends on the operation level and if the electric charging station is constructed by converting a refueling station or not. If a refueling station is converted to a charging station, the construction costs are USD 100,000 and USD 200,000 for the first-level and second-level operations, respectively. For new EV charging stations to be built at candidate nodes without refueling stations (nodes 16 and 17), the construction costs are comparatively higher, at USD 200,000 and USD 400,000 for operational levels 1 and 2, with operational capacities of 300 and 400 vehicles per hour, respectively. Each refueling station operates at a capacity of 600 vehicles per hour ($f_i^t = 600$).

The initial market penetration rate of EVs is assumed to be 5%, and the market potential is expected to be 75%. The two parameters in the demand diffusion model (Equation (15)), ϖ and $\hat{\varsigma}$, are assumed to be 0.03 and 0.5 [72]. The value of time for the travelers is assumed to be 20 (USD/h) [73]. Further, 15% of the ICVs are assumed to require refueling in each hour. For the five-period planning horizon, the available budget is set at USD 100,000 per period. Without the construction of new EV charging stations, the vehicular CO emission rate at the user equilibrium condition of the traffic network is 3.14 tons/h during the planning horizon.

6.2. Model Execution

Given the roadway network for the computational experiment, the enumeration technique that provides a truly optimal solution is utilized to assess the efficiency of the proposed GA for solving the upper-level model. In the model execution process, it took 8.4 min within 100 iterations for the GA to reach convergence. However, 36 h were used by the enumeration technique to generate the final solution. As seen in Figure 3, the gap to optimality (achieved by the enumeration technique) for the GA is 0.57%. This suggests that the proposed GA could help solve the proposed upper-level model with good solution quality while maintaining computational efficiency.

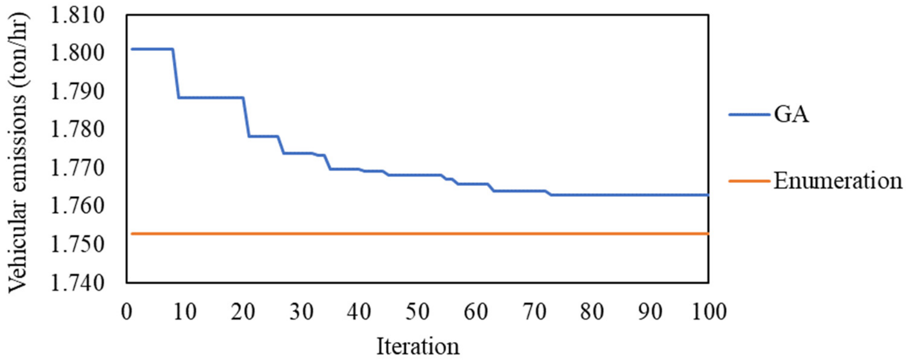

Figure 3. Convergence of solution algorithm.

6.3. Findings

6.3.1. Impacts of Construction Budget

This section examines how the construction budget affects EV market penetration throughout the planning horizon, assuming a vehicle range of 12 miles. Tables 3–5 show the outcomes for three different budget scenarios, with the blue bars indicating EV station construction. In the first scenario (Table 3), termed the "medium-budget scenario", the construction budget is set at USD 100,000 per period for periods 1–5. In the second scenario (Table 3), the "high-budget scenario", the budget is increased to USD 200,000 per period. In the third scenario (Table 4), the "low-budget scenario", the budget is USD 100,000 in periods 1, 3, and 5, and zero for periods 2 and 4. Figure 4 illustrates the construction nodes selected for electric charging stations under each budget scenario. Under the medium-budget scenario, stations operating at level 1 are planned for construction at nodes 10, 18, 12, 22 and 20 in periods 1 through 5, respectively. This results in a vehicular emissions rate of 1.76 ton/h across the planning horizon, which yields a significant CO emissions reduction compared to scenarios without any electric charging station construction (Figure 5). Consequently, establishing new electric charging stations can substantially boost EV market penetration rate, although at a gradually decreasing rate, as shown by the convex trend in Figure 6. This is due to the improvements in the travel costs of EV users. By constructing more electric charging stations in the network, the electric charging stations become more accessible to EV users, and therefore, EV users deviate less from the shortest paths to fulfill their charging needs. This improves EV users' travel costs. Moreover, based on Equation (15), lower travel costs of EV users contribute to higher EV market share in the network. This underscores the impacts of investments in electric charging stations to promote the market share of EVs in the network.

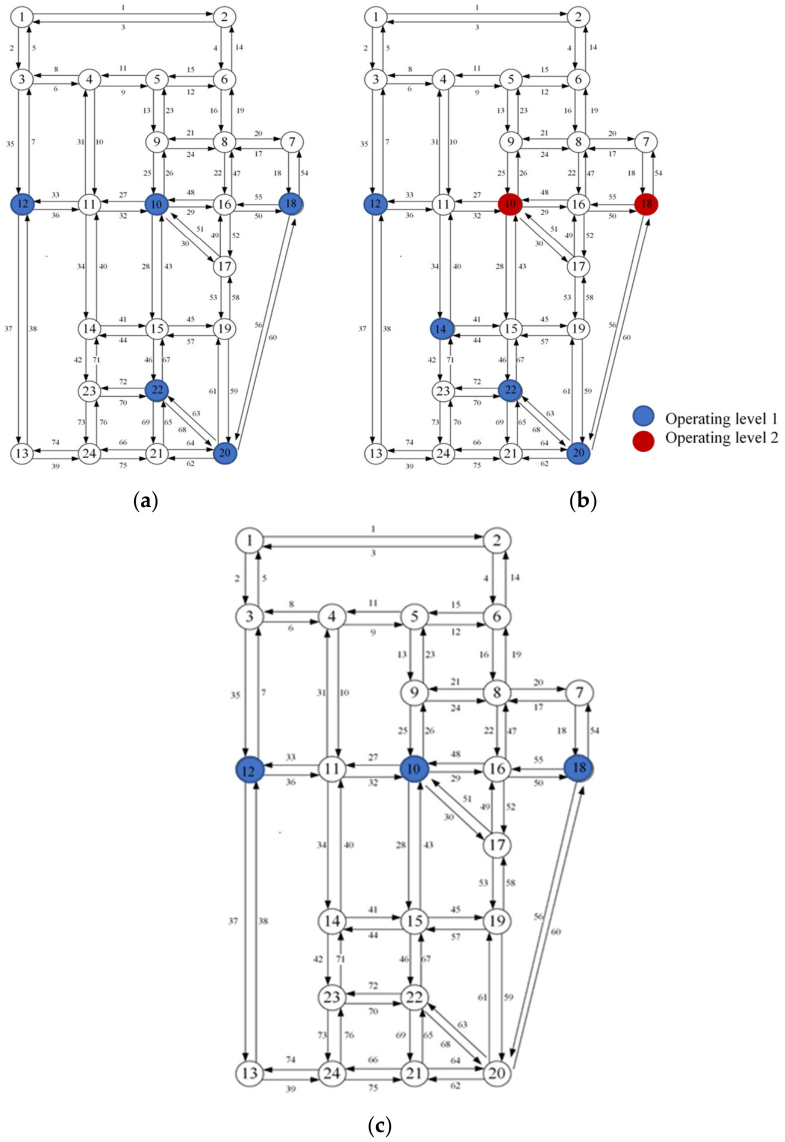

Figure 4. Constructed electric charging stations under different budget scenarios. (**a**) Medium-budget scenario. (**b**) High-budget scenario. (**c**) Low-budget scenario.

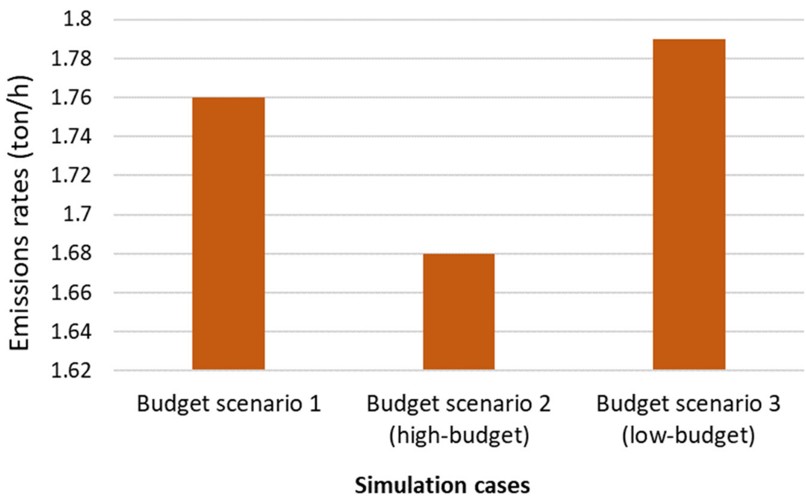

Figure 5. Emissions rates under the budget scenarios.

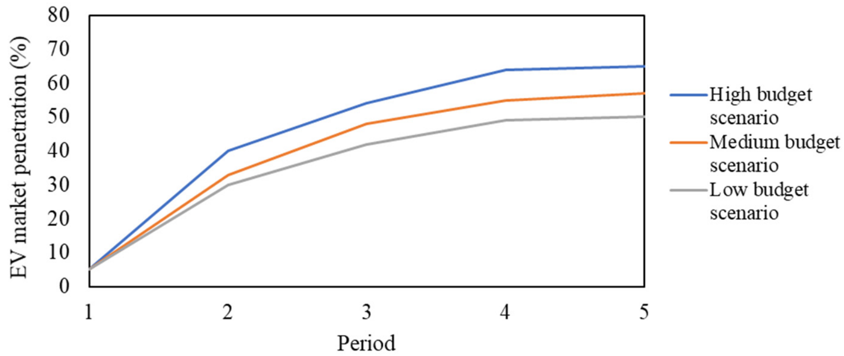

Figure 6. EV market penetration rates under different construction budget levels.

Table 3. EV charging station location scheduling for the medium-budget scenario.

	Candidate Node for EV Charging Station Construction								
Time Period	**4**	**10**	**12**	**14**	**16**	**17**	**18**	**20**	**22**
1									
2									
3									
4									
5									

Electric charging station construction: charging station level 1 (blue color).

Table 4. EV charging station location scheduling for the high-budget scenario.

	Candidate Node for EV Charging Station Construction								
Time Period	**4**	**10**	**12**	**14**	**16**	**17**	**18**	**20**	**22**
1									
2									
3									
4									
5									

Electric charging station construction: charging station level 1 (blue color) and level 2 (red color).

Table 5. EV charging station location scheduling for the low-budget scenario.

	Candidate Node for EV Charging Station Construction								
Time Period	**4**	**10**	**12**	**14**	**16**	**17**	**18**	**20**	**22**
1									
2									
3									
4									
5									

Electric charging station construction: charging station level 1 (blue color).

In the high-budget scenario, some new electric charging stations are determined to be constructed in the network. All of the new electric charging stations operate at level 1, and they are located at nodes 10 and 18 (constructed in the first period), at nodes 12 and 22 (constructed in the second period), and at nodes 20 and 14 (constructed in the third period). Additionally, the solution specifies upgrades for stations at nodes 10 and 18 to level 2 in periods 4 and 5, respectively. Notably, nodes 16 and 17 are excluded from station construction due to the higher construction costs of charging stations at those nodes compared to nodes that have operating refueling stations. The high-budget scenario achieves a vehicular emissions rate of 1.68 ton/h across the planning horizon (Figure 5), indicating that a larger construction budget enables a reduction in emissions and a higher EV market share by expanding EV access to charging stations.

In the low-budget scenario, the new charging stations are prescribed at nodes 10, 18, and 12 in periods 1, 3 and 5, respectively, resulting in a vehicle emissions rate of 1.79 ton/h over the planning horizon (Figure 5). This solution shows that the EV market penetration rate is substantially lower under the low-budget scenario, leading to a higher emissions rate than in the high-budget scenario. This highlights the need for transportation planners to weigh the benefits of increased investment in charging infrastructure against the societal and environmental costs associated with elevated vehicular emissions. To support the Paris Agreement's goals of reducing GHG emissions to specified levels, conducting sensitivity analyses to determine the necessary budget allocations over the planning horizon is essential for achieving these emission standards.

6.3.2. Impact of Driving Range

Next, we examine how different levels of driving range affect EV market penetration rate evolution and emission rates of vehicular CO. In this analysis, three different driving ranges are considered: 12 miles (range 1), 15 miles (range 2) and 25 miles (range 3). Also, it is assumed that per construction period, a budget of USD 100,000 is allocated by transportation agency policies and private sector support for building electric charging stations. Figures 7 and 8 depict how different driving ranges of EVs influence both the EV market penetration rates and the selected locations for electric charging station construction. The findings indicate that the number of charging stations remains consistent across all three driving range scenarios. Although it might seem intuitive that a greater driving range would reduce the need for charging stations, the results suggest that fully utilizing the construction budget contributes to emission reduction. The emissions rates corresponding to driving range scenarios of 1, 2, and 3 are 1.76 ton/h, 1.71 ton/h, and 1.67 ton/h, respectively (Figure 9).

Comparing vehicular emissions across the specified driving ranges with those under the high-budget scenario (1.68 ton/h), it becomes evident that technological advancements in EVs, leading to longer driving ranges, allow for lower emissions with reduced investment in charging infrastructure. Additionally, as the EV driving range extends, the need for EVs to recharge during their trips decreases, and travelers are able to finish their trips with much less deviation from their shortest routes for charging. This contributes to reducing vehicular emissions. Furthermore, increasing EV driving range has a positive effect on market penetration. Numerical results indicate that extending the EV driving range from 12 miles (range 1) to 25 miles (range 2) can boost EV market penetration by as much as 70%.

6.3.3. Impacts on ICV Travel Cost

Figure 10 shows how the transition from ICV toward EV adoption affects the travel costs of travelers in Class 3 (ICV users that require refueling during their trips). This analysis examines two budget scenarios. In the first scenario, a construction budget of USD 100,000 is allocated for each of periods 1–5. In the second scenario, a construction budget of USD 800,000 is considered for each of the planning periods. To evaluate the impact, the study compares the travel costs for ICVs with refueling needs across three cases: (1) without EVs (case 1), (2) with EVs under the first budget scenario (case 2), and (3) with EVs under the second budget scenario (case 3). The average travel costs for ICVs are highest in case 3 compared to cases 1 and 2. In both simulation cases of driving range 1 and driving range 2, the average travel time of ICV users increases over the planning period as a result of rising travel demand. However, in simulation case 3, this average travel time escalates sharply during periods 2–4 for ICV travelers. This occurs because a larger budget allocation for emission reduction and EV adoption, through the conversion of existing refueling stations, limits ICV access to these stations, resulting in considerably higher travel costs for ICVs than in the other cases. In period 5, however, the average travel cost in case 3 drops relative to period 4, thanks to the installation of upgraded charging stations at nodes 10 and 18. Unlike in earlier periods, these refueling stations were not removed in periods 4 and 5, easing demand on available stations and thereby lowering ICV travel costs. This experiment highlights the need for a phased and gradual approach to EV station investment for a smooth EV transition. A rapid reduction in gas stations would drastically increase ICV travel costs, potentially creating unintended challenges for the agency.

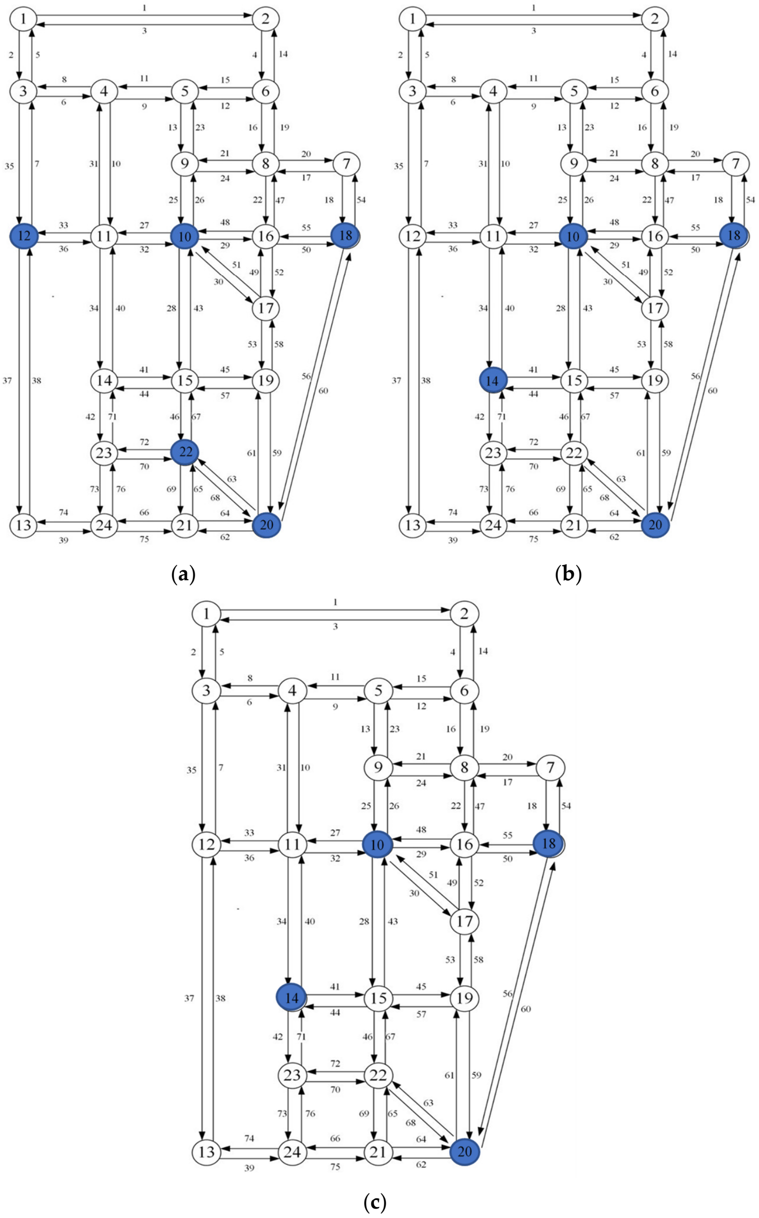

Figure 7. Constructed charging stations for each level of EV driving range. (**a**) Driving range: 12 miles. (**b**) Driving range: 15 miles. (**c**) Driving range: 25 miles.

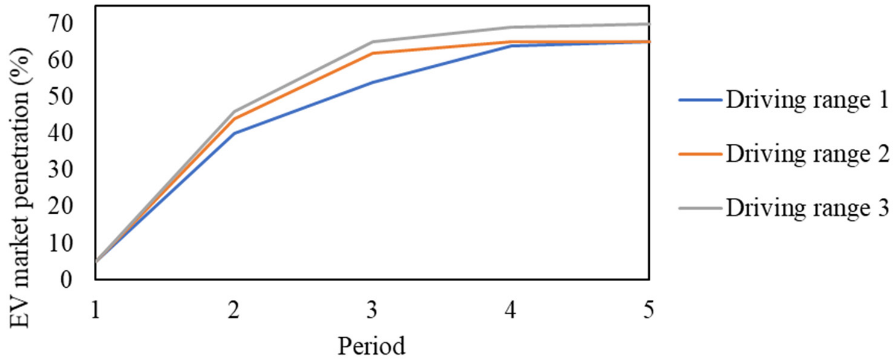

Figure 8. EV market penetration rates under different EV driving ranges.

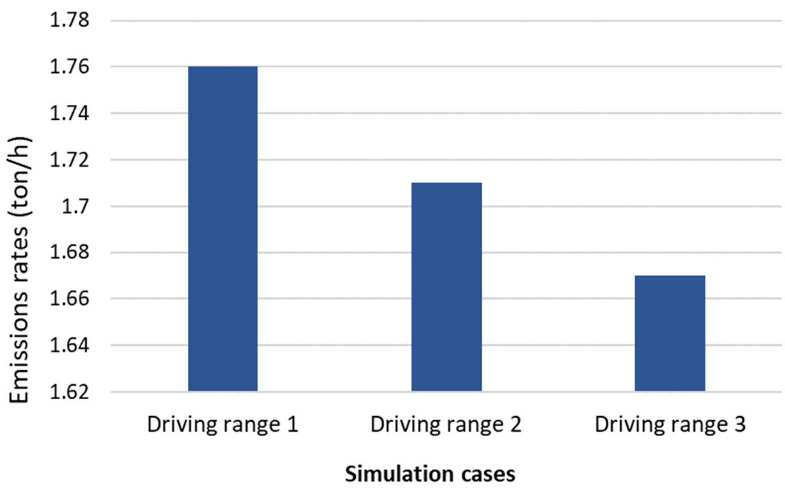

Figure 9. Emissions rates under different driving ranges.

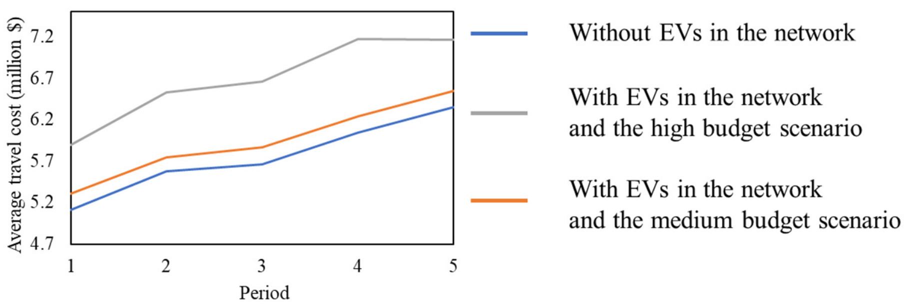

Figure 10. Average travel costs of travelers in Class 2 of ICVs under different electric charging station construction budgets.

7. Conclusions

This paper presents a strategic framework for long-term EV charging station infrastructure planning within an allocated budget, with the goal of reducing urban vehicular emissions. The framework is structured as a bi-level model. In the upper level, transportation agencies and private stakeholders determine the optimal number, placement, and capacities of charging stations to minimize system-wide emissions over the planning period. In response to these decisions, travelers at the lower level choose their shortest routes and their vehicle classes (EV or ICV) based on travel time, traffic conditions, and refueling or charging needs. The diffusion model captures how vehicle choices are influenced by travel time and the costs of EVs and ICVs. A genetic algorithm is applied to solve this bi-level model. Numerical results show that as budgets increase, access to charging stations improves, promoting EV adoption and reducing emissions over time. Additionally, findings suggest that advances in EV range allow planners to meet charging needs with lower investments than would be required without battery improvements.

The strategic framework given in this research is scalable to a variety of city sizes and network topologies. In large cities with high traffic congestion and charging demand, planners should prioritize the deployment of a dense network of charging stations in core, high-traffic locations to optimize access and boost EV adoption. Smaller cities or suburbs, on the other hand, can benefit from a more distributed approach, requiring fewer stations due to lower traffic numbers and greater EV ranges. Furthermore, cities with limited funds can concentrate their first investments on critical corridors or high-demand locations, gradually expanding the network as EV usage grows. This framework provides scalable solutions that can be tailored to the needs of varied urban contexts by adjusting station density, location, and capacity to accommodate local travel patterns and infrastructural constraints.

The strategy framework outlined in this paper is flexible for various city sizes and network structures. In large cities characterized by significant traffic congestion and high charging demand, planners should focus on the construction of a broad network of charging stations in center, high-traffic locations to enhance accessibility and promote electric vehicle adoption. Conversely, smaller cities or suburban regions may benefit from a more decentralized strategy, necessitating fewer stations, owing to lower traffic counts and extended EV ranges. Moreover, municipalities with limited budgets can prioritize initial investments in critical corridors or high-demand regions and progressively extend the network as electric vehicle use increases. This framework offers scalable solutions that can be tailored to accommodate varying urban contexts by modifying station density, location, and capacity to align with local travel patterns and infrastructural limitations.

This research offers several directions for further study. First, this paper assumes no delay in EV charging or ICV refueling. Future studies might relax this assumption, as current EV charging delays (even at fast-charging stations) are significantly longer than ICV refueling times, potentially influencing travelers' vehicle class and route choices. Second, while this paper focuses on reducing vehicular emissions by enhancing access to charging stations, transportation planners should also account for other externalities like traffic congestion and noise. A future model could be developed as a multi-objective optimization problem, allowing transportation planners to assign different weights to these additional evaluation criteria. While the current model provides a robust framework for optimizing the location of EV charging stations, future work could focus on integrating dynamic charging demand (peak and off-peak) and user behavior (e.g., range anxiety) into the decision-making process. Specifically, incorporating time-dependent charging demand patterns, real-time traffic conditions, and user preferences for charging locations would enhance the model's practical applicability. Additionally, further research could explore real-time demand forecasting and adaptive strategies to adjust charging station deployment in response to fluctuating user needs, ensuring a more resilient and efficient charging network. The last research direction could be developing more advanced solution algorithms in the context of electric charging station planning. Developing solution algorithms that have better performance in terms of solution quality, running time, and applicability on large-scale networks is necessary during electric charging infrastructure planning.

Author Contributions: Conceptualization, S.E.S., M.M., G.H.d.A.C. and S.L.; methodology, S.E.S., M.P. and M.M.; software, S.E.S.; validation, S.E.S. and M.M.; formal analysis, S.E.S., M.P. and M.M.; investigation, S.E.S., M.P. and M.M.; resources, S.L.; data curation, S.E.S.; writing—original draft preparation, S.E.S., M.P. and M.M.; writing—review and editing, S.E.S., M.P., M.M., G.H.d.A.C., Z.L. and S.L.; visualization, S.E.S. and M.P.; supervision, M.M., G.H.d.A.C., Z.L. and S.L.; project administration, S.L.; funding acquisition, S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Purdue University's Center for Connected and Automated Transportation (CCAT), a part of the larger CCAT consortium that is a USDOT Region 5 University Transportation Center funded by the U.S. Department of Transportation, Award #69A3551747105. The paper is also a part of the Center for Innovation in Control, Optimization, and Networks (ICON), and the Autonomous and Connected Systems (ACS) initiatives at Purdue University's College of Engineering. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein, and do not necessarily reflect the official views or policies of the sponsoring organization.

Data Availability Statement: All data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. IPCC. *Climate Change: Working Group III: Mitigation of Climate Change*; IPCC: Geneva, Switzerland, 2007.
2. Pourgholamali, M.; Davatgari, A.; Wang, J.; Benny, D.; Miralinaghi, M.; Labi, S. *Facilitating Electric Propulsion of Autonomous Vehicles Through Efficient Design of a Charging-Facility Network*; CCAT Report #40; The Center for Connected and Automated Transportation, Purdue University: West Lafayette, IN, USA, 2022.
3. U.S. Energy Information Administration. *Annual Energy Outlook 2014*; U.S. Energy Information Administration: Washington, DC, USA, 2014.
4. Neshat, N.; Kaya, M.; Zare, S.G. Exploratory policy analysis for electric vehicle adoption in European countries: A multi-agent-based modelling approach. *J. Clean. Prod.* **2023**, *414*, 137401. [CrossRef]
5. Jia, Z.; Wei, N.; Yin, J.; Zhao, X.; Wu, L.; Zhang, Y.; Peng, J.; Wang, T.; Yang, Z.; Zhang, Q.; et al. Energy saving and emission reduction effects from the application of green light optimized speed advisory on plug-in hybrid vehicle. *J. Clean. Prod.* **2023**, *412*, 137452. [CrossRef]
6. Racherla, K.; Waight, M. Addressing EMI in Electric Cars with Radio Tuner Architecture [Future Directions]. *IEEE Consum. Electron. Mag.* **2018**, *7*, 15–124. [CrossRef]
7. CarEdge. Electric vehicle sales and market share (US—Updated monthly). Available online: https://caredge.com/guides/electric-vehicle-market-share-and-sales (accessed on 2 December 2023).
8. Wu, S.; Pang, A. Optimal scheduling strategy for orderly charging and discharging of electric vehicles based on spatio-temporal characteristics. *J. Clean. Prod.* **2023**, *392*, 136318. [CrossRef]
9. Alternative Fuels Data Center. Electric Registrations by State. 2022. Available online: https://afdc.energy.gov/data/widgets/10962 (accessed on 2 September 2023).
10. Highway Statistics Series. 2022. Available online: https://www.fhwa.dot.gov/policyinformation/statistics.cfm (accessed on 2 September 2023).
11. Indiana Department of Transportation. *Indiana Electric Vehicle Infrastructure Deployment Plan*; Indiana Department of Transportation: Indianapolis, IN, USA, 2022.
12. Michigan Department of Transportation. Michigan State Plan for Electric Vehicle Infrastructure Deployment. 2022. Available online: https://www.fhwa.dot.gov/environment/nevi/ev_deployment_plans/mi_nevi_plan.pdf (accessed on 20 November 2024).
13. New York Department of Transportation. *New York State National Electric Vehicle Infrastructure Formula Program*; New York Department of Transportation: Albany, NY, USA, 2022. Available online: https://www.fhwa.dot.gov/environment/nevi/ev_deployment_plans/ny_nevi_plan.pdf (accessed on 20 November 2024).
14. Texas Department of Transportation. *Texas Electric Vehicle Infrastructure Plan*; Texas Department of Transportation: Austin, TX, USA, 2022.
15. Pan, Y.; Fang, W.; Zhang, W. Development of an energy consumption prediction model for battery electric vehicles in real-world driving: A combined approach of short-trip segment division and deep learning. *J. Clean. Prod.* **2023**, *400*, 136742. [CrossRef]
16. USA Facts. Available online: https://usafacts.org/articles/how-many-electric-vehicle-charging-stations-are-there-in-the-us/ (accessed on 23 December 2023).
17. Statista. Available online: https://www.statista.com/statistics/525107/number-of-gasoline-stations-in-the-united-states/ (accessed on 23 December 2023).
18. Le Sage, J. Electric vehicle charging points to rise significantly in 2018. *USA Today*, 29 December 2017.

19. FHWA. Historic Step: All Fifty States Plus D.C. and Puerto Rico Greenlit to Move EV Charging Networks Forward, Covering 75,000 Miles of Highway | FHWA. Available online: https://highways.dot.gov/newsroom/historic-step-all-fifty-states-plus-dc-and-puerto-rico-greenlit-move-ev-charging-networks (accessed on 20 November 2024).
20. Xiong, H.; Shahidehpour, M.; Shi, Y.; Luo, F.; Guo, C. Multi-period Planning for Renewable Electric Vehicle Charging Stations in Coordinated Power Distribution and Transportation Networks with Non-anticipativity Constraints. *IEEE Trans. Transp. Electrif.* **2024**. [CrossRef]
21. Li, K.; Shao, C.; Huang, X.; Shahidehpour, M.; Wang, X. Day-Ahead Charging Capacity Market for Power Distribution Network with Electric Vehicle Charging Stations. *IEEE Trans. Power Syst.* **2024**. [CrossRef]
22. Qian, T.; Shao, C.; Li, X.; Wang, X.; Shahidehpour, M. Enhanced Coordinated Operations of Electric Power and Transportation Networks via EV Charging Services. *IEEE Trans. Smart Grid* **2020**, *11*, 3019–3030. [CrossRef]
23. Wang, X.; Shahidehpour, M.; Jiang, C.; Li, Z. Coordinated Planning Strategy for Electric Vehicle Charging Stations and Coupled Traffic-Electric Networks. *IEEE Trans. Power Syst.* **2019**, *34*, 268–279. [CrossRef]
24. Lambert, F. Gas Station Removes Gas Pumps to Make Space for Electric Car-Charging Stations—Electrek. Available online: https://electrek.co/2019/09/27/gas-station-removes-gas-pumps-for-electric-car-charging-stations/ (accessed on 19 November 2020).
25. Çelik, S.; Ok, Ş. Electric vehicle charging stations: Model, algorithm, simulation, location, and capacity planning. *Heliyon* **2024**, *10*, e12848. [CrossRef]
26. Kavianipour, M.; Verbas, O.; Rostami, A.; Soltanpour, A.; Gurumurthy, K.M.; Ghamami, M.; Zockaie, A. Deploying fast charging infrastructure for electric vehicles in urban networks: An activity-based approach. *Transp. Res. Rec.* **2024**, *2678*, 416–435. [CrossRef]
27. Soltanpour, A.; Ghamami, M.; Nicknam, M.; Ganji, M.; Tian, W. Charging infrastructure and schedule planning for a public transit network with a mixed fleet of electric and diesel buses. *Transp. Res. Rec.* **2023**, *2677*, 1053–1071. [CrossRef]
28. Pourgholamali, M.; Homem de Almeida Correia, G.; Tarighati Tabesh, M.; Esmaeilzadeh Seilabi, S.; Miralinaghi, M.; Labi, S. Robust Design of Electric Charging Infrastructure Locations under Travel Demand Uncertainty and Driving Range Heterogeneity. *J. Infrastruct. Syst.* **2023**, *29*, 04023016. [CrossRef]
29. He, M.; Wang, S.; Zhuge, C. A data-driven large-scale micro-simulation approach to deploying and operating wireless charging lanes. *Transp. Res. Part D Transp. Environ.* **2023**, *121*, 103835. [CrossRef]
30. Yıldız, B.; Olcaytu, E.; Şen, A. The urban recharging infrastructure design problem with stochastic demands and capacitated charging stations. *Transp. Res. Part B Methodol.* **2019**, *119*, 22–44. [CrossRef]
31. Tran, C.Q.; Keyvan-Ekbatani, M.; Ngoduy, D.; Watling, D. Dynamic wireless charging lanes location model in urban networks considering route choices. *Transp. Res. Part C Emerg. Technol.* **2022**, *139*, 103652. [CrossRef]
32. Kuby, M.; Lim, S. Location of Alternative-Fuel Stations Using the Flow-Refueling Location Model and Dispersion of Candidate Sites on Arcs. *Netw. Spat. Econ.* **2007**, *7*, 129–152. [CrossRef]
33. Upchurch, C.; Kuby, M.; Lim, S. A Model for Location of Capacitated Alternative-Fuel Stations. *Geogr. Anal.* **2009**, *41*, 85–106. [CrossRef]
34. Kuby, M.; Lines, L.; Schultz, R.; Xie, Z.; Kim, J.-G.; Lim, S. Optimization of hydrogen stations in Florida using the Flow-Refueling Location Model. *Int. J. Hydrogen Energy* **2009**, *34*, 6045–6064. [CrossRef]
35. Lim, S.; Kuby, M. Heuristic algorithms for siting alternative-fuel stations using the Flow-Refueling Location Model. *Eur. J. Oper. Res.* **2010**, *204*, 51–61. [CrossRef]
36. Kim, J.-G.; Kuby, M. The deviation-flow refueling location model for optimizing a network of refueling stations. *Int. J. Hydrogen Energy* **2012**, *37*, 5406–5420. [CrossRef]
37. Capar, I.; Kuby, M.; Leon, V.J.; Tsai, Y.-J. An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. *Eur. J. Oper. Res.* **2013**, *227*, 142–151. [CrossRef]
38. Miralinaghi, M.; Keskin, B.B.; Lou, Y.; Roshandeh, A.M. Capacitated Refueling Station Location Problem with Traffic Deviations Over Multiple Time Periods. *Netw. Spat. Econ.* **2016**, *17*, 129–151. [CrossRef]
39. Zeng, B.; Wang, W.; Zhang, W.; Wang, Y.; Tang, C.; Wang, J. Optimal configuration planning of vehicle sharing station-based electro-hydrogen micro-energy systems for transportation decarbonization. *J. Clean. Prod.* **2023**, *387*, 135906. [CrossRef]
40. Miralinaghi, M.; Lou, Y.; Keskin, B.B.; Zarrinmehr, A.; Shabanpour, R. Refueling station location problem with traffic deviation considering route choice and demand uncertainty. *Int. J. Hydrogen Energy* **2017**, *42*, 3335–3351. [CrossRef]
41. Calandra, D.; Wang, T.D.; Cane, M.; Alfiero, S. Management of hydrogen mobility challenges: A systematic literature review. *J. Clean. Prod.* **2023**, *410*, 137305. [CrossRef]
42. Wang, Y.W.; Wang, C.R. Locating passenger vehicle refueling stations. *Transp. Res. Part E Logist. Transp. Rev.* **2010**, *46*, 791–801. [CrossRef]
43. Huang, Y.; Li, S.; Qian, Z.S. Optimal Deployment of Alternative Fueling Stations on Transportation Networks Considering Deviation Paths. *Netw. Spat. Econ.* **2015**, *15*, 183–204. [CrossRef]

44. Ghamami, M.; Zockaie, A.; Nie, Y. A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. *Transp. Res. Part C Emerg. Technol.* **2016**, *68*, 389–402. [CrossRef]
45. Wu, F.; Sioshansi, R. A stochastic flow-capturing model to optimize the location of fast-charging stations with uncertain electric vehicle flows. *Transp. Res. Part D Transp. Environ.* **2017**, *53*, 354–376. [CrossRef]
46. Anjos, M.F.; Gendron, B.; Joyce-Moniz, M. Increasing electric vehicle adoption through the optimal deployment of fast-charging stations for local and long-distance travel. *Eur. J. Oper. Res.* **2020**, *285*, 263–278. [CrossRef]
47. Chen, T.D.; Kockelman, K.M.; Khan, M. Locating Electric Vehicle Charging Stations. *Transp. Res. Rec. J. Transp. Res. Board* **2013**, *2385*, 28–36. [CrossRef]
48. Chen, Z.; He, F.; Yin, Y. Optimal deployment of charging lanes for electric vehicles in transportation networks. *Transp. Res. Part B Methodol.* **2016**, *91*, 344–365. [CrossRef]
49. Zheng, H.; He, X.; Li, Y.; Peeta, S. Traffic Equilibrium and Charging Facility Locations for Electric Vehicles. *Netw. Spat. Econ.* **2017**, *17*, 435–457. [CrossRef]
50. Liu, H.; Wang, D.Z.W. Locating multiple types of charging facilities for battery electric vehicles. *Transp. Res. Part B Methodol.* **2017**, *103*, 30–55. [CrossRef]
51. Mubarak, M.; Üster, H.; Abdelghany, K.; Khodayar, M. Strategic network design and analysis for in-motion wireless charging of electric vehicles. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *145*, 102179. [CrossRef]
52. Yi, Z.; Chen, B.; Liu, X.C.; Wei, R.; Chen, J.; Chen, Z. An agent-based modeling approach for public charging demand estimation and charging station location optimization at urban scale. *Comput. Environ. Urban Syst.* **2023**, *101*, 101949. [CrossRef]
53. Muyesseroglu, A.; Argun, I.D.; Kayakutlu, G. Electric vehicle charge station layout planning: A case study in Istanbul Technical University campus. *Manag. Decis. Econ.* **2023**, *44*, 1767–1778. [CrossRef]
54. Campana, M.; Inga, E. Optimal deployment of fast-charging stations for electric vehicles considering the sizing of the electrical distribution network and traffic condition. *Energy Rep.* **2023**, *9*, 5246–5268. [CrossRef]
55. Zeng, X.; Xie, C.; Xu, M.; Chen, Z. Optimal en-route charging station locations for electric vehicles with heterogeneous range anxiety. *Transp. Res. Part C Emerg. Technol.* **2024**, *158*, 104459. [CrossRef]
56. Yin, Y.; Lawphongpanich, S. Internalizing emission externality on road networks. *Transp. Res. Part D Transp. Environ.* **2006**, *11*, 292–301. [CrossRef]
57. Ma, R.; Ban, X.J.; Szeto, W.Y. Emission Modeling and Pricing on Single-destination Dynamic Traffic Networks. *Transp. Res. Part B Methodol.* **2017**, *100*, 255–283. [CrossRef]
58. Pourgholamali, M.; Miralinaghi, M.; Seilabi, S.E.; Labi, S. Sustainable deployment of autonomous vehicles dedicated lanes in urban traffic networks. *Sustain. Cities Soc.* **2023**, *99*, 104969. [CrossRef]
59. Li, T.; Xu, M.; Sun, H.; Xiong, J.; Dou, X. Stochastic ridesharing equilibrium problem with compensation optimization. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *170*, 102999. [CrossRef]
60. Park, S.Y.; Kim, J.W.; Lee, D.H. Development of a market penetration forecasting model for Hydrogen Fuel Cell Vehicles considering infrastructure and cost reduction effects. *Energy Policy* **2011**, *39*, 3307–3315. [CrossRef]
61. Nieuwenhuijsen, J.; de Almeida Correia, G.H.; Milakis, D.; van Arem, B.; van Daalen, E. Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics. *Transp. Res. Part C Emerg. Technol.* **2018**, *86*, 300–327. [CrossRef]
62. Bazaraa, M.S.; Sherali, H.D.; Shetty, C.M. *Nonlinear Programming: Theory and Algorithms*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
63. Zhang, L.; Lawphongpanich, S.; Yin, Y. An active-set algorithm for discrete network design problems. In *Transportation and Traffic Theory 2009: Golden Jubilee*; William, H.K.L., Wong, S.C., Lo Hong, K., Eds.; Springer: New York, NY, USA, 2009; pp. 283–300.
64. Goldberg, D.E. *Genetic Algorithms in Search, Optimization, and Machine Learning*; Addison-Wesley Publishing Company, Inc.: Reading, MA, USA, 1988.
65. Hosseininasab, S.M.; Shetab-Boushehri, S.N. Integration of selecting and scheduling urban road construction projects as a time-dependent discrete network design problem. *Eur. J. Oper. Res.* **2015**, *246*, 762–771. [CrossRef]
66. Lua, R.; de Almeida Correia, G.H.; Zhao, X.; Liang, X.; Lv, Y. Performance of one-way carsharing systems under combined strategy of pricing and relocations. *Transp. B Transp. Dyn.* **2021**, *9*, 134–152. [CrossRef]
67. Wang, X.; Zhu, H.; Luo, X.; Chang, S.; Guan, X. A novel optimal dispatch strategy for hybrid energy ship power system based on the improved NSGA-II algorithm. *Electr. Power Syst. Res.* **2024**, *232*, 110385. [CrossRef]
68. Bahrami, S.; Aashtiani, H.Z.; Nourinejad, M.; Roorda, M.J. A complementarity equilibrium model for electric vehicles with charging. *Int. J. Transp. Sci. Technol.* **2017**, *6*, 255–271. [CrossRef]
69. LeBlanc, L.J.; Morlok, E.K.; Pierskalla, W.P. An Efficient Approach to Solving the Road Network Equilibrium Traffic Assignment Problem. *Transp. Res.* **1975**, *9*, 309–318. [CrossRef]
70. Xie, C.; Jiang, N. Relay Requirement and Traffic Assignment of Electric Vehicles. *Comput.-Aided Civ. Infrastruct. Eng.* **2016**, *31*, 580–598. [CrossRef]

71. Jing, W.; An, K.; Ramezani, M.; Kim, I. Location Design of Electric Vehicle Charging Facilities: A Path-Distance Constrained Stochastic User Equilibrium Approach. *J. Adv. Transp.* **2017**, *2017*, 4252946. [CrossRef]
72. Chen, Z.; He, F.; Zhang, L.; Yin, Y. Optimal deployment of autonomous vehicle lanes with endogenous market penetration. *Transp. Res. Part C Emerg. Technol.* **2016**, *72*, 143–156. [CrossRef]
73. FHWA. *The Value of Travel Time Savings: Departmental Guidance for Conducting Economic Evaluations*; FHWA: Washington, DC, USA, 2016.