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Abstract: The rising demand for electric vehicles (EVs), motivated by their environmental benefits, is generating an increased need for EV charging infrastructure. Also, it has been recognized that the adequacy of such infrastructure helps promote EV use. Therefore, to facilitate EV adoption, governments seek guidance on continued investments in EV charging infrastructure development. Such investment decisions, which include EV charging station locations and capacities, and the timing of such investments require robust estimates of future travel demand and EV battery range constraints. This paper develops and implements a framework to establish an optimal schedule and locations for new charging stations and decommissioning gasoline refueling stations over a long-term planning horizon, considering the uncertainty in future travel demand forecasts and the driving range heterogeneity of EVs. A robust mathematical model is proposed to solve the problem by minimizing not only the worst-case total system travel cost but also the total penalty for unused capacities of charging stations. This study uses an adaptation of the cutting-plane method to solve the proposed model. Based on two key decision criteria (travelers' cost and charging supply sufficiency), the results indicate that the robust scheme outperforms its deterministic counterpart. **DOI: 10.1061/JITSE4.ISENG-2191.**

Author keywords: Electric vehicles (EVs); Charging stations; Robust design; Demand uncertainty; Range heterogeneity.

Introduction

Global concerns associated with the environment, climate change, and energy security continue to motivate the transition from fossil fuel vehicles [also referred to as internal combustion engine vehicles (ICEV)] to other fuel types. Of the various types of alternative fuel vehicles, electric vehicles (EVs) have been proven to be a viable option to replace ICEVs.

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To support the ICEV-EV transition, governments and automakers globally continue to make efforts, through policy and design, to increase the EV market share. For example, the United Kingdom and France seek to end ICEV sales by 2040 (Racherla and Waight 2018). In spite of global efforts, the current EV market share is still limited worldwide. For example, according to recent data, the EV market share is less than 2% in the United States even though several incentive programs to promote EVs have been implemented (Alternative Fuels Data Center 2022; FHWA 2022a).

The lack of electric charging stations is well recognized as one of the barriers to EV adoption in the US (Indiana DOT 2022; Michigan DOT 2022; New York DOT 2022; Texas DOT 2022). Researchers have found that in addition to initiatives including enhancements to battery capacity, reduction of recharging time, and increase in time-to-depletion, the provision of adequate electric charging stations helps reduce the driving range anxiety of EV users and ultimately promotes the EV penetration rate in the US (Cihat Onat et al. 2018; Coffman et al. 2017; Desai et al. 2021; Fauble et al. 2022; Funke et al. 2019; Huang and Kockelman 2020). Franke and Krems (2013) argued that unless public authorities and private entities provide adequate charging stations to satisfy EV charging demand, customers will not be willing to purchase EVs. Due to the importance of charging stations, the US government recently provided a $5 billion budget for building EV charging infrastructure across the nation's highway network (FHWA 2022b).

Such promotion of EVs is considered urgent in the current era for at least two reasons. First, the reduction of greenhouse gases is a major goal of the Infrastructure Investment and Jobs Act (IIJA) (Public Law 117-58), an unprecedented transportation legislation signed by President Biden in 2021. That legislation specifically targeted climate change and therefore required the Federal Energy Regulatory Commission to require each state to consider measures to promote greater transportation electrification, including the promotion of EV charging and improving the customer experience with EV charging. With their zero-emissions feature, EVs are more environmentally friendly, pose less threat to the climate, and therefore are of great interest to both public agencies and road users concerned with their impact (Gardner et al. 2013). Second, the shift from gasoline to electric propulsion is a part of the broader national goal of energy security, an issue that has gained prominence in the wake of the Russia-Ukraine war.

Three mechanisms for EV charging have been discussed in the literature: (1) static charging (using charging stations), (2) inductive/wireless charging (Chen et al. 2016), and (3) battery swapping (Adler et al. 2016). Based on the power level of the charging equipment, the static charging method can be further classified into three levels: Level 1, suitable for residential locations, charges EVs using 120-V alternating current (AC) outlets and the charging duration can reach 20 h; Level 2, suitable for public parking, uses 208-V commercial AC electrical services with a charging duration of a few hours; and Level 3, which uses 480-V AC power service, is referred to as *direct current (DC) fast charging* and the charging duration is less than 1 h (Khalid et al. 2021).

Similar to the case for all infrastructure systems, the development of EV charging infrastructure must be accompanied by a good balance between investment level and usage. On the one hand, inadequate charging stations will cause delays and frustration for EV users; on the other hand, an excessive number of stations will lead to excess idle time and underutilization of the stations, and ultimately, a waste of resources. Constructing adequate electric stations at well-chosen locations will decrease driving range anxiety and, therefore, is paramount to facilitating EV promotion (Cihat Onat et al. 2018; Coffman et al. 2017; Desai et al. 2021; Fauble et al. 2022; Funke et al. 2019; Guo et al. 2018; Huang and Kockelman 2020; Miralinaghi et al. 2016, 2017, 2020).

In this paper, we propose a model for the optimal location of Level-3 electric charging stations in order to satisfy the charging demand of travelers for intercity trips during the transition period on the path toward full EV fleet market share. Due to the fast-charging technology of these types of EV charging stations, they are suitable for rural networks. Therefore, travelers can charge their EVs in a few minutes and continue their journey. In addition to prospective new locations for the construction of electric charging stations, current gasoline (including diesel) refueling stations serve as candidate locations for installing EV charging stations. However, it is expected that ICEVs (which patronize gasoline refueling stations) will continue to constitute a major part of the roadway traffic fleet during most of the transition period. Therefore, their refueling needs will have to be addressed. As the market share of ICEVs decreases during the transition period, an increasing number of gasoline refueling stations will experience low demand and ultimately become candidates for decommissioning or repurposing as EV charging stations. In this study, therefore, we assume that refueling stations are decommissioned only when their demand falls below a certain threshold. Moreover, there is great variability in the driving ranges across the different EV classes and across different manufacturers. For example, the driving ranges of the Nissan Leaf and Tesla Model X are approximately 241 and 482 km (150 and 300 mi), respectively (Insideevs 2018). As such, this study accounts for the driving range heterogeneity of EVs.

In practice, the task of locating EV charging infrastructure on a road network has been identified as a constituent aspect of the strategic plans of service providers and governments over long planning horizons. Due to the long-term horizon that is typical of agency strategic plans, the service provider needs to carry out a strategic network design that accommodates EV charging demand. Such demand is influenced by the EV adoption rate and the driving behavior of travelers. Over the next few decades, the EV adoption rate is generally expected to increase, but the rate of increase is uncertain due to factors including initial price sensitivity, energy cost, range reliability, and charging infrastructure availability (Liu and Lin 2016). Further, the fast-growing technological advancements and disruptive technologies, including electric automated vehicles, are expected to exacerbate the uncertainty in travel demand and driving patterns over the next few decades. Given the uncertainty in the EV adoption rate and driving behavior, it can be argued that the EV charging demand can also be expected to be highly uncertain.

Literature Review

There is an extensive body of research on electric vehicle charging station planning. These studies cover different aspects, including charging technologies (Brenna et al. 2020; Fisher et al. 2014; Shevchenko et al. 2019); travelers' behaviors and preferences in electrification (Guo et al. 2021, 2022); and optimal charging station configuration (Bai et al. 2019; Kchaou-Boujelben and Gicquel 2020; Kınay et al. 2021; Yıldız et al. 2019). This study only relates to the past studies on optimal charging station planning, which can be classified into two groups based on the EV charging demand assumptions. The first group deals with locating stations under the assumption of deterministic refueling demand. Zheng et al. (2017) determined the optimal locations of EV charging stations with the objective of minimizing the total system travel time and electricity consumption of travelers. Arslan and Karaşan (2016) developed a mixed-integer program for the EV charging station location problem, in which the goal of the road infrastructure agency is to maximize the distance traveled by EVs. They solved the problem by using the Benders decomposition technique with Pareto-optimal cut implementations, which significantly reduced the computational time. He et al. (2018) proposed a bilevel framework for EV charging stations. The goal was to maximize the flow usage of the charging stations in the upper level. Anjos et al. (2020) focused on the interaction of EV adaption and the availability of charging stations over a long-term planning horizon. In this regard, they proposed a mixed-integer linear program model to determine the optimal construction of electric vehicle charging stations by maximizing the number of EVs in the network. They presented a rolling horizon-based heuristic to solve the problem. Bai et al. (2019) studied the EV charging station location problem under the circumstances of a low EV penetration rate in the network. They used a vehicle's GPS data set to identify some potential charging station locations. Based on the identified potential locations, the optimal charging station locations were determined through a bilevel framework that minimized the construction cost and maximized the electric charging service quality. To solve the presented bilevel framework, a hybrid algorithm combining nondominated sorting genetic algorithm II (NGSA-II) and neighborhood search was applied. Kınay et al. (2021) studied both the optimal design of charging stations and the optimal routing of EVs. In this regard, two different problems were presented. The first sought to minimize the construction cost of charging stations and total enroute recharging of EVs. The second model only minimized the total enroute charging of EVs. The authors applied a Bender decomposition algorithm to solve the problems. To support intercity trips of EVs, Fakhrmoosavi et al. (2021) studied the optimal charging station planning within the state of Michigan. The authors determined the optimal charging station configuration that minimizes construction costs and travelers' delays. Khaksari et al. (2021) studied the optimal capacity planning of electric charging stations by proposing a mixed-integer program that minimized the construction cost of the charging stations. Moreover, their mixed-integer program ensured that the quality of the electric charging service for EVs, in terms of the probability of delay in complementation of charging, was maintained above specific levels.

The second group deals with uncertainty in both traffic network demand and supply (e.g., link capacity). Sathaye and Kelley (2013) proposed a continuous optimization approach for constructing electric charging stations along highway corridors with the objective of minimizing the distance traveled by EVs to recharge at charging stations, subject to a budget constraint. Hosseini and MirHassani (2015) developed a multiperiod two-stage decision framework to locate permanent and portable EV charging facilities. The portable facilities can be relocated across the periods. In this framework, the road infrastructure agency determines the optimal locations of charging stations given the uncertainty in path flows on the traffic network. The present paper addresses the uncertainty of the recharging demand of travelers during their intercity trips and, therefore, can be placed in the second group of studies. Yıldız et al. (2019) studied the optimal configuration of electric charging stations that minimize the construction cost of electric charging stations, accounting for demand uncertainty in the optimal charging station planning and adopting a scenario-based approach to model such uncertainty. Kadri et al. (2020) proposed an optimization problem to maximize the expected served EV flows over a long-term planning horizon. The researchers incorporated the uncertainties about the electric recharging demand of EVs into the charging station planning and adopted a multistage stochastic integer programming approach based on a scenario tree to represent recharging demand uncertainty. Kchaou-Boujelben and Gicquel (2020) focused on driving range uncertainty in the optimal planning of electric charging stations. More specifically, they captured the uncertainties in the energy consumption of EVs and the energy availability of EV batteries.

Study Objectives and Scope

In this paper, we duly and explicitly consider the uncertainty in EV charging demand over a long-term planning horizon (that is, on the order of several years) to locate the EV charging stations to serve intercity travel. As stated earlier, the uncertainty in electric charging demand can be attributed to uncertainty in travel demand forecasts over a long-term planning horizon. In practice, there is inherent uncertainty in forecasting travel demand over a long-term planning horizon, and the accuracy of travel demand forecasts declines with lengthening the planning horizon. In other words, near-term travel demand forecasts are more accurate or reliable compared to medium- or long-term forecasts over the planning horizon. This demand uncertainty could be attributed to changes in land use, economic, and demographic characteristics. However, this has not been addressed in the context of EV charging station location and therefore represents another gap in the literature. In mathematical programming, there are two methods to address such uncertainty. The first, stochastic programming, assumes different probabilities of occurrence for different scenarios (Dantzig 1955). However, estimating this probability distribution is difficult in practice. The second method proposes the concept of a robust approach that optimizes the system against the worst-case scenario while circumventing the need to estimate the probabilities of different scenarios (Bertsimas and Sim 2003). This has been applied previously for network design with demand uncertainty (Lou et al. 2009). In this study, we adopt the second method because we seek to develop a robust design of EV charging station locations under travel demand uncertainty. This paper formulates this as a multiobjective optimization problem that seeks to reduce the maximum total system travel time and the costs associated with unused charging station capacities over a long planning horizon.

Therefore, the contributions of this study to the literature are as follows. A robust design for a network of electric charging stations is developed to address the uncertainty of travelers' refueling and electric charging demands. This is a holistic framework that prepares the charging infrastructure during the transition stage by gradually decommissioning the existing refueling stations in the context of intercity trips. The third contribution is the consideration of the driving range heterogeneity of electric vehicle batteries.

The remaining sections are structured as follows. First, we present the methodology. Next, we briefly discuss the solution algorithm, followed by numerical experiments that compare the performances of robust and deterministic designs of electric charging station locations under travel demand uncertainty forecasts. Finally, the study's insights and concluding remarks are provided.

Methodology

Let $G = (N, A)$ represent the road network. We divide the planning horizon into T periods, which comprise the total duration of the planning horizon (typically, several years). Let τ denote the set of periods. The mixed-traffic scenario consists of EVs with different driving ranges and ICEVs. Let M denote the set of vehicle types with cardinality $|M|$ where class 1 denotes ICEVs. Let $m > 1$ denote different classes of EVs with different driving ranges, where $R^{m,t}$ is the driving range of EVs of class m in period t. The notations used in this paper are defined in the "Notation" section.

In practice, forecasts of travel demand are uncertain over a long-term planning horizon. This study assumes that it belongs to an uncertainty set. The travel demand uncertainty set for each vehicle class m for each origin-destination (O-D) pair (r, s) in each period t is denoted by $E^{m,t}_{r,s}$ in which $e = 1$ represents the deterministic travel demand scenario that can be used for analysis without considering travel demand uncertainty. It can denote the peak hour for travel demand. Let $\boldsymbol{p}$ denote the vector of aforementioned binary variables, that is $\boldsymbol{p} = \{p^{m,e,t}_{r,s}, \forall (r, s) \in W, \forall m \in M, e \in E^{m,t}_{r,s}, \forall t \in \tau\}$. For each vehicle class m traveling between O-D pair (r, s) in period t, there is only one realized travel demand scenario, that is $\sum_{e \in E^{m,t}_{r,s}} p^{m,e,t}_{r,s} = 1$. Given these notations, the travel demand uncertainty set Q can be formulated as follows:

$$Q = \left\{ \boldsymbol{q} \Big| \sum_{e \in E^{m,t}_{r,s}} q^{m,e,t}_{r,s} p^{m,e,t}_{r,s} = q^{m,t}_{r,s}, \sum_{e \in E^{m,t}_{r,s}} p^{m,e,t}_{r,s} = 1, p^{m,e,t}_{r,s} \in \{0, 1\} \right\} \tag{1}$$

where $\boldsymbol{q} = (q^{m,e,t}_{r,s}, \forall (r, s) \in W, \forall m \in M, e \in E^{m,t}_{r,s}, \forall t \in \tau)$ denotes the set of potential travel demand vectors. In deriving the optimal strategy for charging and refueling stations, if the road infrastructure agency does not account for the travel demand uncertainty and instead only incorporates a certain vector of travel demand (such as the peak-hour travel demand), then the robust scheme is reduced to a conventional *deterministic* scheme.

This study assumes that charging/refueling stations are located on nodes or links (specifically, besides the links). Travelers experience a delay after recharging/refueling. To capture the impact of charging/refueling delays of travelers and the operational capacity

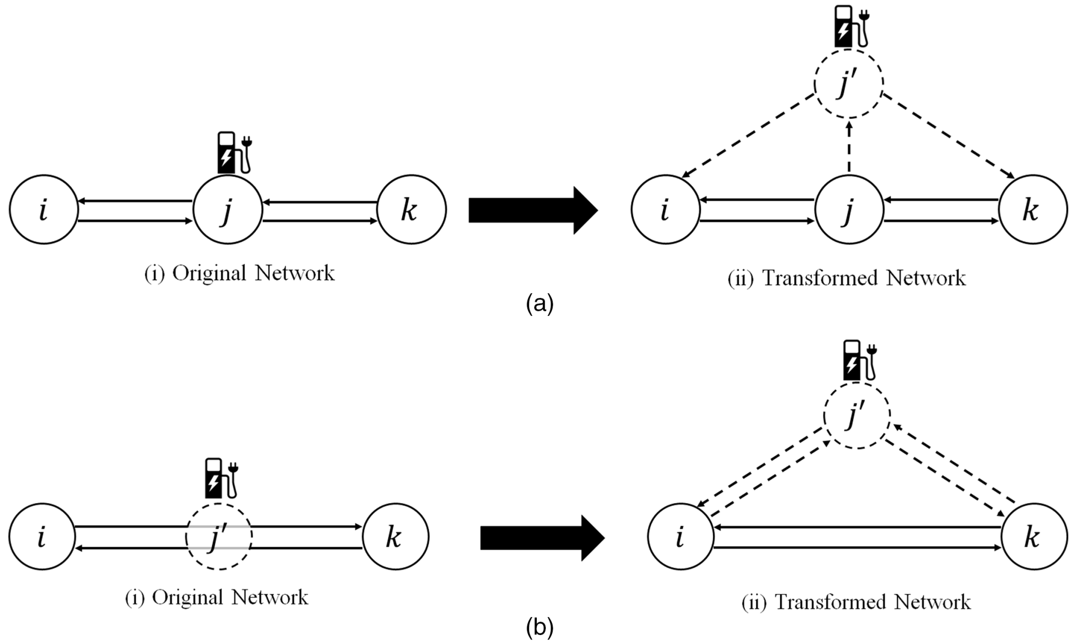

Fig. 1. Transformation of traffic network: (a) electric charging station on a node; and (b) electric charging station on a link.

of stations, the road network configuration is modified. For each node or link with a charging/refueling station (either candidate or existing), we include a dummy node and certain dummy link(s) depending on the connection of the original node or links to other nodes in the road network. The set of dummy candidate nodes for charging stations is represented by $\bar{N}$. The set of dummy nodes with existing refueling and charging stations are denoted by $\bar{\bar{N}}$ and $\check{N}$, respectively. $\check{N}$ is assumed to be a subset of $\bar{N}$. Let $\check{A}$ denote the set of dummy links.

The network transformation is illustrated in Fig. 1. Fig. 1(a) represents the original network where the charging station is located on node j. To capture the impact of charging delay and capacity of station j, we include dummy node j' with the charging station [Fig. 1(a)]. Since node j is connected to nodes i and k, we include two dummy Links (j', i) and (j', k). The delay of the dummy Link (j, j'), $\hat{c}^{m,t}_{j,j'}$, is equal to the charging delay of EV travelers. The length of the dummy link is set to zero to ensure that it does not impact the driving range. Travelers who traverse through Link (j, j') for recharging can continue their trips by using Links (j', i), and (j', k) as they are identical to the Links (j, i), and (j, k), respectively. Similarly, a dummy node j' is added to the network to capture the charging or refueling delay, when a charging or refueling station is located at the link [Fig. 1(b)]. The dummy node j' is connected to nodes i and j by dummy links that have delays equal to the charge or refuel delays of EV and ICEV travelers, respectively. If travelers do not need to charge or refuel, they do not need to traverse through dummy links and use only the actual links of the network [Links (i, k) or (k, i)]. Besides, it is assumed that the refueling/charging stations serve travelers with finite operational capacities. The capacity of the newly constructed or existing charging stations is independent of the operational capacity of the refueling stations.

This mathematical program involves multiobjective optimization; therefore, the weights of total system travel time (H_1) and the total penalty of unused charging stations' capacities (H_2) are denoted by ϕ_1 and ϕ_2, respectively. We define Ψ as the penalty for unused capacities of charging stations. Let Δ^t be a factor for calculating the present value of costs in period t that reflects the interest rates through the long-term planning horizon. Then, Δ^t is equal to $1/(1+\pi)^{t-1}$. Let κ denote the parameter that converts the costs of travelers and unused charging station capacity from an hourly basis to the basis of each period duration (e.g., several days). The robust design of the charging network with refueling infrastructure can be formulated as the following min-max problem (MMP1):

$$\min_{\boldsymbol{\varphi},\boldsymbol{\theta}}\left(\max_{\boldsymbol{p},\boldsymbol{v}}\,(\phi_1\cdot\mathrm{H}_1+\phi_2\cdot\mathrm{H}_2)\right) \tag{2}$$

Upper-Level Model

$$\mathrm{H}_1=\sum_{t\in\tau}\Delta^t\cdot\kappa\cdot\beta^t\cdot\left(\sum_{(i,j)\in A}\nu^t_{i,j}\cdot c^t_{i,j}+\sum_{m\in M}\sum_{(i,j)\in\check{A}}v^t_{i,j}\cdot\hat{c}^{m,t}_{i,j}\right) \tag{3}$$

$$\mathrm{H}_2=\sum_{t\in\tau}\Psi\cdot\Delta^t\cdot\kappa\cdot\sum_{j:(i,j)\in\check{A}|j\in\bar{N}}\;\sum_{i:(i,j)\in\check{A}}(n_j-\nu^t_{i,j}) \tag{4}$$

$$\varphi^1_i=1\quad\forall i\in\bar{\bar{N}} \tag{5}$$

$$\varphi^t_i\le\varphi^{t-1}_i\quad\forall i\in\bar{\bar{N}},\forall t\in\Gamma \tag{6}$$

$$\sum_{i\in\bar{N}}k^t_i\theta^1_i\le B^1 \tag{7}$$

$$\sum_{i\in\bar{N}}k^t_i(\theta^t_i-\theta^{t-1}_i)\le B^t\quad\forall t\in\Gamma,t>1 \tag{8}$$

$$\theta^t_i=1\quad\forall i\in\check{N},\forall t\in\Gamma \tag{9}$$

$$\theta^t_i\ge\theta^{t-1}_i\quad\forall i\in\bar{N},\forall t\in\Gamma \tag{10}$$

$$\bar{h}_j \cdot \varphi_j^t \leq v_{i,j}^t \quad \forall i \in N, \forall j \in \bar{\bar{N}}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{11}$$

$$\nu_{i,j}^t \leq n_j \cdot \varphi_j^t \quad \forall i \in N, \forall j \in \bar{\bar{N}}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{12}$$

$$\nu_{i,j}^t \leq n_j \cdot \theta_j^t \quad \forall i \in N, \forall j \in \bar{N}, \forall (i,j) \in \check{A}, \forall t \in \Gamma \tag{13}$$

$$\theta_i^t \in \{0,1\} \quad \forall i \in \bar{N}, \forall t \in \tag{14}$$

$$\varphi_i^t \in \{0,1\} \quad \forall i \in \bar{\bar{N}}, \forall t \in \Gamma \tag{15}$$

Lower-Level Model

$$f_{ij}^{w,t,1} \cdot \left(c_{ij}^t(\nu_{ij}^t) + \mu_i^{w,t,1} - \mu_j^{w,t,1}\right) = 0 \quad \forall (i,j) \in A, \forall w, \forall t \tag{16}$$

$$c_{ij}^t(\nu_{ij}^t) + \mu_i^{w,t,1} - \mu_j^{w,t,1} \geq 0 \quad \forall (i,j) \in A, \forall w, \forall t \tag{17}$$

$$f_{ij}^{w,t,m} \cdot \left(c_{ij}^t(\nu_{ij}^t) + \zeta_{ij}^{w,t,m} + \mu_i^{w,t,m} - \mu_j^{w,t,m}\right) = 0$$
$$\forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{18}$$

$$c_{ij}^t(\nu_{ij}^t) + \zeta_{ij}^{w,t,m} + \mu_i^{w,t,m} - \mu_j^{w,t,m} \geq 0 \quad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{19}$$

$$f_{ij}^{w,t,m} \leq \Lambda e_{ij}^{w,t,m} \quad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{20}$$

$$\zeta_{ij}^{w,t,m} \leq \Lambda(1 - e_{ij}^{w,t,m}) \quad \forall (i,j) \in A, \forall w, \forall t, m > 1 \tag{21}$$

$$\mu_s^{w,t,m} = 0 \quad \forall w, \forall s, \forall t, \forall m \tag{22}$$

$$v_{i,j}^t = \sum_{w \in W} \sum_{m \in M} f_{ij}^{w,t,m} \quad \forall t \tag{23}$$

$$\sum_{j:(j,i) \in A} f_{ji}^{w,t,m} - \sum_{j:(i,j) \in A} f_{ij}^{w,t,m} = q_i^{w,t,m} \quad \forall w, \forall i, \forall t, \forall m \tag{24}$$

$$\zeta_{ij}^{w,t,m}, f_{ij}^{w,t,m}, p_i^{w,t,m} \geq 0 \quad \forall (i,j), \forall w, \forall t, \forall m \tag{25}$$

where n_j = charging/refueling capacity of the charging/refueling station located at node j. The goal of the presented model is to minimize the total weighted costs of charging station construction, the worst-case sum of system travel time, refueling and charging delays, and the overall penalty due to unused capacities of the charging stations [Eqs. (2)–(4)]. Constraints Eq. (5) ensure that refueling stations exist in the first period and can be used by ICEVs. Constraints Eq. (6) state that if the refueling station of node i stops working in period $t-1$, then it cannot be patronized by ICEVs for the rest of the planning horizon. Constraints Eqs. (7) and (8) ensure that the monetary budget for the construction of the new charging stations is satisfied in each period. Constraints Eq. (9) state that the existing charging stations are available for charging through the entire planning horizon. Constraints Eq. (10) ensure that once a charging station is constructed in a period, it remains available for charging in subsequent periods. Constraints Eq. (11) ensure that the refueling station of node j works in period t if its demand is greater than or equal to $\bar{h}_j$. Constraints Eq. (12) are the capacity constraints of refueling stations that state that the number of vehicles that refuel at node j in period t [i.e., traverse through the dummy Link (i,j)] is less than n_j if the refueling station is available in that period. It also ensures that after removing the refueling station at node j, the refueling demand of that node becomes zero. Constraints Eq. (13) are identical to constraints Eq. (12) except that they apply to the charging stations, meaning that the number of vehicles that recharge at node j in period t is less than n_j if the charging station located at node j is available for charging in period t, and 0 otherwise. Constraints Eqs. (14) and (15) state that θ_i^t and φ_i^t are binary variables.

The second body of the model addresses the route choice behavior of travelers [Eqs. (16)–(25)]. Constraints Eqs. (16) and (17) are the user equilibrium conditions for ICEV users that ensure that if ICEV users of each O-D pair use Link (i,j), it belongs to the path between that O-D pair with minimum travel cost. Similarly, constraints Eqs. (18) and (19) are the user equilibrium conditions for EV users. Constraints Eq. (20) ensures that if Link (i,j) does not belong to the feasible path between an O-D pair, the flow of EVs is zero. Similarly, constraints Eq. (21) imposes an excessive travel cost on a Link (i,j) that is not a part of the feasible EV path. Constraints Eq. (22) indicates that travel time at the origin is equal to zero. Eq. (23) calculates the total traffic flow of Link (i,j) in period t. Constraints Eq. (24) ensures demand conservation, and constraints Eq. (25) ensures the nonnegativity of $\zeta_{ij}^{w,t,m}$, $f_{ij}^{w,t,m}$, and $p_i^{w,t,m}$.

An important component of the aforementioned formulation [Eqs. (2)–(25)] is the feasible path of EVs ($e_{ij}^{w,m,t}$). Considering the heterogeneous driving range of EVs, the feasible paths of EVs ($e_{ij}^{w,m,t}$) are derived as a set of mixed-integer linear programs [Eqs. (26)–(42)]

$$u_j^{w,m,t} \geq u'^{w,m,t}_i + L_{ij} - \Lambda(1 - e_{ij}^{w,m,t}) \quad \forall (i,j) \in A, \forall w, \forall m, \forall t, \forall i, j \tag{26}$$

$$u_j^{w,t} \leq u'^{w,t}_i + L_{ij} + \Lambda(1 - e_{ij}^{w,m,t}) \quad \forall (i,j) \in A, \forall w, \forall m, \forall t, \forall i, j \tag{27}$$

$$u_i^{w,m,t} \leq R^{m,t} \quad \forall t, \forall w, \forall m, \forall i \tag{28}$$

$$u'^{w,m,t}_i \geq u_i^{w,m,t} - \Lambda\theta_i^t \quad \forall t, \forall w, \forall m > 1, \forall i \in N - (\check{N} \cup \bar{\bar{N}}) \tag{29}$$

$$u'^{w,m,t}_i \leq u_i^{w,m,t} + \Lambda\theta_i^t \quad \forall t, \forall w, \forall m > 1, \forall i \in N - (\check{N} \cup \bar{\bar{N}}) \tag{30}$$

$$u'^{w,m,t}_i \leq \Lambda(1 - \theta_i^t) \quad \forall t, \forall w, \forall m > 1, \forall i \in \bar{N} \tag{31}$$

$$u'^{w,m,t}_i = 0 \quad \forall i \in \check{N}, \forall m > 1, \forall t, \forall w \tag{32}$$

$$u'^{w,m,t}_i \leq \Lambda(1 - \varphi_j^t) \quad \forall i \in \bar{\bar{N}}, \forall m = 1, \forall t, \forall w \tag{33}$$

$$u'^{w,m,t}_s = 0 \quad \forall s | (s,r) \in W, \forall m, \forall t, \forall w \tag{34}$$

$$u_s^{w,m,t} = 0 \quad \forall s | (s,r) \in W, \forall m, \forall t, \forall w \tag{35}$$

$$-\Lambda(1 - e_{ij}^{w,m,t}) + \sum_{j:(j,i) \in A} f_{ji}^{w,t,m} \leq g_i^{w,t,m}$$
$$\forall t, \forall w, \forall m > 1, \forall i \in \check{N} \cup \bar{N} \tag{36}$$

$$\Lambda(1 - e_{ij}^{w,m,t}) + \sum_{j:(j,i) \in A} f_{ji}^{w,t,m} \geq g_i^{w,t,m}$$
$$\forall t, \forall s, \forall m > 1, \forall i \in \check{N} \cup \bar{N} \tag{37}$$

$$\sum_{w,m} g_i^{w,t,m} = h_i^t \quad \forall i, \forall w, \forall t \tag{38}$$

$$h_i^t \leq \bar{n}_j \theta_i^t \quad \forall t, \forall i \in \bar{N} \cup \check{N} \tag{39}$$

$$\sum_{j,w} f_{ji}^{w,t,1} \leq \bar{\bar{n}}_i \varphi_i^t \quad \forall t, \forall i \in \bar{\bar{N}} \tag{40}$$

$$u'^{w,t}_i, u_i^{w,t}, g_i^{w,t,m}, h_i^t \geq 0 \quad \forall t, \forall w, \forall i \tag{41}$$

$$e_{ij}^{w,t,m} \in \{0,1\} \quad \forall t, \forall w, \forall (i,j) \in A \tag{42}$$

Constraints Eqs. (26) and (27) calculate the distance that travelers traveled from the last visited charging station, after visiting node j and just before visiting node i. Constraints Eq. (28) ensure that the traveled distance of EVs ($u_j^{w,m,t}$) is less than the driving range in period t. Constraints Eqs. (29) and (30) ensure that if a charging station is not located at node i, the traveled distance from the last visited charging station just before visiting node i ($u_i^{w,t}$) and after visiting node i ($u'^{w,t}_i$) is equal. If a charging station is constructed at node i, $u'^{w,t}_i$ is equal to zero [constraints Eq. (31)]. This implies that the traveled distance is set to zero after visiting the constructed charging stations. Similarly, if there is a charging station at candidate node i, $u'^{w,t}_i$ is equal to zero [constraints Eq. (32)]. Constraints Eqs. (34) and (35) ensure that ($u_i^{w,t}$) and ($u'^{w,t}_i$) are zero at the origin of the trips. Constraints Eqs. (36) and (37) calculate the flow of EVs originated from node s in a charging station i in period t. Constraints Eq. (38) calculates the total volume of EVs that recharge at station i and ensures that the total volume of EVs that recharge at charging station i does not exceed the capacity of that charging station [constraints Eq. (39)]. Constraints Eq. (40) ensures that when a refueling station is decommissioned, it does not serve the ICEVs anymore. Constraints Eq. (41) ensures the nonnegativity of $u'^{w,t}_i, u_i^{w,t}, g_i^{w,t,m}$, and h_i^t. $e_{ij}^{w,t,3}$ and $y_i^{1,t}$ are binary variables according to constraints Eq. (42).

Solution Algorithm

The proposed MMP1 [Eqs. (2)–(42)] contains two types of binary variables and is classified as a mixed-integer problem. It cannot be solved in polynomial time, and therefore, is described as nondeterministic polynomial hard (NP-hard). The cutting-plane scheme (Lou et al. 2009) is used to solve MMP1 Eqs. (2)–(42) by addressing two subproblems during each iteration. The first subproblem determines the optimal timeline of locating new charging stations and decommissioning the existing refueling stations [Eqs. (1)–(42)] based on a subset of the travel demand uncertainty set. The second subproblem generates a new worst-case travel demand scenario. To implement this scheme, first, we need to reformulate MMP1 as the following mixed-integer problem (MMP2):

$$L_2 = \min_{\boldsymbol{\varphi},\boldsymbol{\theta}}(\omega) \tag{43}$$

$$\omega \geq \phi_1 \cdot \sum_{t\in\tau} \Delta^t \cdot \beta^t \cdot \kappa \cdot \left(\sum_{(i,j)\in A} v_{i,j}^{t,q} \cdot c_{i,j}^t + \sum_{m\in M} \sum_{(i,j)\in\check{A}} v_{i,j}^{t,q} \cdot \hat{c}_{i,j}^t \right)$$
$$+ \phi_2 \cdot \sum_{t\in\tau} \Delta^t \cdot \Psi \cdot \kappa \cdot \left(\sum_{j:(i,j)\in\check{A}|j\in\bar{N}} \sum_{i:(i,j)\in\check{A}} (n_j - v_{i,j}^{t,q}) \right) \quad \forall q \in Q \tag{44}$$

$$\nu^q \in \Omega(\boldsymbol{q}) \quad \forall q \in Q \tag{45}$$

where the superscript $(\cdot)^q$ denotes the variables that are associated with a specific travel demand uncertainty vector $q \in Q$. Although the number of feasible scenarios for the travel demand of each vehicle class m of O-D pair (r, s) in period t is particularly small, the number of vectors in the travel demand uncertainty set (Q) is generally very large. In MMP2, Eqs. (11)–(42), which present the user equilibrium (UE) conditions, need to be written for each $q \in Q$. To prevent presenting repetitive equations, Eq. (45) represents the Eqs. (11)–(42) for each $q \in Q$. Therefore, $\Omega(\boldsymbol{q})$ represents the UE link flows for each $q \in Q$. Due to the tremendous increase in the number of constraints, we solve the relaxed MMP2 using a subset $\tilde{Q} \subseteq Q$ that includes a restricted number of travel demand vectors. The idea of the cutting-plane scheme is to update the subset $\tilde{Q}$ unless we are unable to identify a travel demand vector that leads to a higher weighted summation of total travel cost and penalties of unused charging stations' capacities compared to the current solution (i.e., the worst-case travel demand scenario). Fig. 2 presents a simplified flowchart of the cutting-plane scheme.

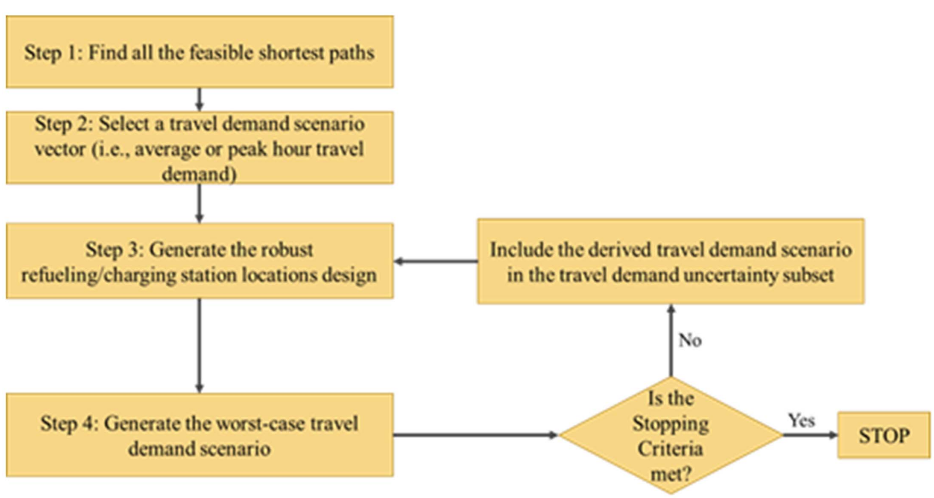

Fig. 2. Flowchart of the cutting-plane scheme.

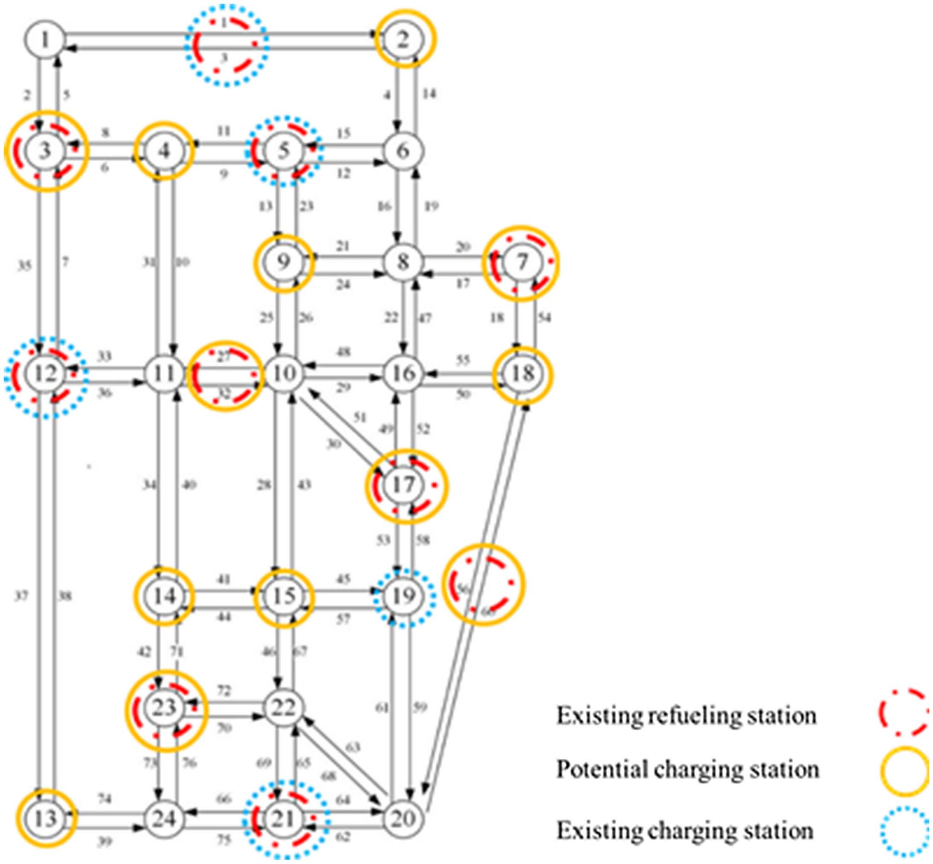

Fig. 3. Sioux Falls network refueling and charging stations.

Numerical Experiments

This section conducts numerical experiments using the well-known Sioux Falls, South Dakota, city road network (Fig. 3), which has 24 nodes and 76 links. The road agency seeks the optimal timeline for constructing new EV charging stations and decommissioning the existing refueling stations over the planning horizon. The horizon is assumed to be equal to 18 years, with six time periods of 3-year duration each. The characteristics of this network have been modified to mimic intercity travels compared to the characteristics proposed by LeBlanc et al. (1975). The link characteristics (travel times and lengths) and the aggregate peak-hour travel demand of each O-D pair in the first period are listed in Table 1 and Fig. 4, respectively. The value of time (β^t) is assumed to be equal to \$20/h in the first period (US DOT 2016). It is assumed that this value increases by \$2 in each period and reaches \$30/h in Period 6. The aggregate travel demand for each O-D pair is assumed to grow by 5% in each period. There are two classes of EVs with different driving ranges: 150 and 200 mi in Period 1 for EV types 1 and 2, respectively. These ranges increase in each period to reach 200 and 250 mi in Period 6 for EV types 1 and 2, respectively (Mazda US 2022; Nissan US 2022; Volvo Cars 2022). The driving range of ICEV vehicles is considered to be equal to 250 mi for all periods. The EV class market penetration starts at 2.5% of aggregate travel demand of each O-D pair in the first period and increases constantly until reaching 40% in Period 6. On the other hand, the market penetration of ICEV vehicles starts at 95% and decreases to 20% in the last period. The proposed algorithm (Fig. 2) is coded in the General Algebraic Modeling System (GAMS version 25.1.3) using CPLEX solver. The results were obtained using a Core i7 processor with a 2.6 GHZ CPU and 8 GB RAM. Based on the settings used in the analysis, the average computational time of the cutting-plane scheme is 148 s.

It is assumed that the network has 10 existing refueling stations located at Nodes 3, 5, 7, 12, 17, 21, and 23, and also at Links (1,2), (10,11), and (18,20). There are also five existing charging stations at Nodes 5, 12, 19, 21, and Link (1,2). Fig. 3 illustrates 13 candidate locations for constructing new charging stations, which are Nodes 2, 3, 4, 7, 9, 13, 14, 15, 17, 18, 23, and Links (10,11) and (18,20). The construction costs of new charging stations are assumed to be identical for all candidate locations. This cost starts at \$500,000 in the first period, increases by \$100,000 in each period, and reaches \$1 million in the sixth period. The construction budget for new charging stations in each period is equal to \$1.5 million in Periods 1–4, and equal to \$1 million for Periods 5 and 6. The charging delay is assumed to be equal to 30 min in the first period for electric vehicles (i.e., $m > 1$) as the approximation for the delay of the current fast-charging stations (Mazda US 2022; Nissan US 2022; Volvo Cars 2022). The charging delay is assumed to decrease during the planning horizon due to technological advancements, and reach 10 min in Period 6. For ICEVs (i.e., $m = 1$), the refueling delay is assumed to be constant and equal to 5 min during the planning horizon. The operational capacities (n_j) of charging and refueling stations are 60 and 150 vehicles per hour, respectively. The penalty for the unused capacity of a charging station is assumed to be equal to \$10 per hour.

In this case study, we assume that $\phi_1 = \phi_2 = 1$ for the weights in the objective function. The constant interest rate (π) for each period during the entire planning horizon is assumed to be equal to 5%. Hence, Δ^t is equal to $1/1.05^{t-1}$. Furthermore, κ equals to

Table 1. Link characteristics of Sioux Falls network

Link No.	From	To	Travel time (min)	Length (mi)
1	1	2	60.34	71.52
2	1	3	43.94	52.08
3	2	1	60.34	71.52
4	2	6	52.35	62.04
5	3	1	43.94	52.08
6	3	4	43.64	51.72
7	3	12	41.92	49.68
8	4	3	43.64	51.72
9	4	5	21.87	25.92
10	4	11	65.41	77.52
11	5	4	21.87	25.92
12	5	6	42.22	50.04
13	5	9	50.93	60.36
14	6	2	52.35	62.04
15	6	5	42.22	50.04
16	6	8	21.97	26.04
17	7	8	25.31	30.00
18	7	18	22.07	26.16
19	8	6	21.97	26.04
20	8	7	25.31	30.00
21	8	9	97.30	115.32
22	8	16	48.80	57.84
23	9	5	50.93	60.36
24	9	8	97.30	115.32
25	9	10	27.84	33.00
26	10	9	27.84	33.00
27	10	11	50.62	60.00
28	10	15	59.43	70.44
29	10	16	45.56	54.00
30	10	17	81.41	96.48
31	11	4	65.41	77.52
32	11	10	50.62	60.00
33	11	12	65.41	77.52
34	11	14	44.75	53.04
35	12	3	41.92	49.68
36	12	11	65.41	77.52
37	12	13	30.17	35.76
38	13	12	30.17	35.76
39	13	24	37.67	44.64
40	14	11	44.75	53.04
41	14	15	45.77	54.24
42	14	23	43.03	51.00
43	15	10	59.43	70.44
44	15	14	45.77	54.24
45	15	19	35.44	42.00
46	15	22	35.44	42.00
47	16	8	48.80	57.84
48	16	10	45.56	54.00
49	16	17	16.91	20.04
50	16	18	27.24	32.28
51	17	10	81.41	96.48
52	17	16	16.91	20.04
53	17	19	23.39	27.72
54	18	7	22.07	26.16
55	18	16	27.24	32.28
56	18	20	45.16	53.52
57	19	15	35.44	42.00
58	19	17	23.39	27.72
59	19	20	40.40	47.88
60	20	18	45.16	53.52
61	20	19	40.40	47.88
62	20	21	57.92	68.64
63	20	22	47.69	56.52
64	21	20	57.92	68.64
65	21	22	16.91	20.04
66	21	24	33.31	39.48
67	22	15	35.44	42.00
68	22	20	47.69	56.52
69	22	21	16.91	20.04
70	22	23	40.50	48.00
71	23	14	43.03	51.00
72	23	22	40.50	48.00
73	23	24	19.04	22.56
74	24	13	37.67	44.64
75	24	21	33.31	39.48
76	24	23	19.04	22.56

26,280 (that is, $24 \times 365 \times 3$) to convert the hourly based costs to the basis of each period duration (i.e., 3 years). The conversion factor presents the system costs in a way that is more representative of real-world applications, and its value does not affect the analysis outcomes. For implementation, this factor could be adjusted to fit and represent the real-world conditions associated with those applications. Finally, it is assumed that up to five shortest paths can be utilized for each O-D pair and vehicle class in each period ($k = 5$).

First, we compare the obtained locations and decommissioning timelines under deterministic and robust schemes. Travel demand uncertainty set for O-D pair w, vehicle class m in time period t consists of (1) travel demand scenario of peak hour, (2) low travel demand scenario, (3) medium travel demand scenario, and (4) high travel demand scenario. Travel demand Scenarios (2)–(4) are derived by multiplying the travel demand Scenario 1, as the benchmark, with random parameters that are generated based on the uniform distribution. The domain of the low travel demand scenario is [0.95, 1] in Period 1 while the lower bound decreases consistently during the transition horizon until it reaches [0.7, 1] in Period 6. The domains of medium and high travel demand scenarios are [1, 1.05] and [1, 1.1] in Period 1, respectively, while the upperbounds increase during the transition horizon until they reach [1, 1.3] and [1, 1.6] for the medium and high travel demand scenarios, respectively.

The results present the developed optimal timelines for locating the new charging stations and for decommissioning existing refueling stations under deterministic and robust schemes. Under the robust scheme, there are three additional constructed charging stations compared to the deterministic scheme during the planning horizon. This is due to the higher conservatism of the road agencies, who consider the worst-case travel demand scenario in the optimal design. Under the robust scheme, charging stations are constructed in the most congested areas of the network (Nodes 7, 9, and 18) with higher demands expected for this area in the first period. With the exception of Node 7, this result stands in contrast with the result from the deterministic scheme, which proposes to build the charging stations in the less congested areas of the region and on the borders of the network (Nodes 2 and 13).

Furthermore, both schemes suggest almost identical designs for decommissioning the existing refueling stations, except for Period 5. Both schemes suggest decommissioning refueling stations located at Node 23, Link (10,11), Node 3, and Node 17 in Periods 2, 3, 4, and 6. Under the deterministic scheme, the refueling station on Node 12 must be decommissioned in Period 5 while the robust scheme suggests decommissioning the refueling station located at Link (18,20) in Period 5. This similarity is due to the fact that the total operational capacity of refueling stations is significantly higher than the refueling demand, and considering the worst cases

Origin Zone	Destination Zone																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	3	6	18	9	12	15	24	18	42	18	9	18	9	15	18	15	6	9	9	3	12	9	6
2	3	0	3	9	3	15	6	15	9	18	6	6	9	3	6	12	9	3	3	6	3	6	3	3
3	6	3	0	9	3	9	3	6	6	9	9	9	6	3	3	6	3	0	3	3	3	3	3	3
4	18	9	9	0	15	15	15	21	24	36	45	21	18	15	15	24	15	3	9	12	6	12	15	9
5	9	3	3	15	0	9	6	18	24	30	18	6	6	6	9	18	9		6	6	3	6	6	3
6	12	15	9	15	9	0	12	24	12	24	12	9	9	6	9	30	18	3	9	12	3	9	6	3
7	15	6	3	15	6	12	0	33	18	57	15	24	15	9	15	42	30	6	15	18	9	18	6	3
8	24	15	6	21	18	24	33	0	27	48	27	18	18	12	21	66	42	9	21	27	12	18	12	6
9	18	9	6	24	24	12	18	27	0	84	45	21	18	18	30	45	30	6	15	21	12	21	18	6
10	42	18	9	36	30	24	57	48	84	0	120	63	57	66	120	132	117	21	54	78	39	81	54	27
11	18	6	9	45	18	12	15	27	45	120	0	45	30	48	45	42	30	6	15	21	15	33	42	18
12	9	6	9	21	6	9	24	18	21	63	45	0	42	21	24	21	21	6	9	15	12	24	21	15
13	18	9	6	18	6	9	15	18	18	57	30	42	0	18	21	21	18	3	12	21	18	39	24	24
14	9	3	3	15	6	6	9	12	18	66	48	21	18	0	39	21	21	3	12	15	12	36	33	12
15	15	6	3	15	9	9	15	21	30	120	45	24	21	39	0	39	45	9	24	33	24	78	30	15
16	18	12	6	24	18	30	42	66	45	132	42	21	21	21	39	0	84	15	42	51	18	36	18	9
17	15	9	3	15	9	18	30	42	30	117	30	21	18	21	45	84	0	21	51	51	21	51	18	9
18	6	3		3	3	3	6	9	6	21	6	6	3	3	9	15	21	0	12	15	3	12	3	3
19	9	3	3	9	6	9	15	21	15	54	15	9	12	12	24	42	51	12	0	39	15	39	12	6
20	9	6	3	12	6	12	18	27	21	78	21	15	21	15	33	51	51	15	39	0	39	75	21	15
21	3	3	3	6	3	3	9	12	12	39	15	12	18	12	24	18	21	3	15	39	0	57	21	18
22	12	6	3	12	6	9	18	18	21	81	33	24	39	36	78	36	51	12	39	75	57	0	66	36
23	9	3	3	15	6	6	6	12	18	54	42	21	24	33	30	18	18	3	12	21	21	66	0	24
24	6	3	3	9	3	3	3	6	6	27	18	15	24	12	15	9	9	3	6	15	18	36	24	0

Fig. 4. Aggregate travel demand for each origin-destination (O-D) pair in Period 1.

of travel demand vectors in the robust scheme compared to the deterministic scheme, does not make a significant difference in the list of existing refueling stations to be decommissioned under either scheme.

Three Monte Carlo simulations are implemented to compare the performance of the deterministic and robust schemes under uncertainty in the long-term travel demand forecasts. In this analysis, we generate 1,000 travel demand vectors for each simulation based on the different distributions that use travel demand Scenarios (1)–(4). The distributions for Simulations 1–3 include (1) discrete uniform distribution with identical occurrence probability for each travel demand scenario (that is, 0.25); (2) pessimistically asymmetric distribution with higher occurrence probability for medium (that is, 0.4) and high (that is, 0.4) travel demand scenarios and lower occurrence probability for peak-hour (that is, 0.15) and low (that is, 0.05) travel demand scenarios; and (3) optimistically asymmetric distribution with higher occurrence probability for low (that is, 0.4) and peak-hour (that is, 0.4) travel demand scenarios and lower occurrence probabilities for medium (0.15) and high (0.05) travel demand scenarios, respectively. For each simulation instance, if the proposed design is not capable of addressing the charging demand, the simulation instance is reimplemented with the assumption that the road infrastructure agency increases the capacities of charging stations by 50% under such travel demands. Since this expansion should be implemented in the short-term due to the lack of a long-term plan (referred to as *unplanned capacity expansion*), the expansion cost for each charging station is assumed to be equal to the construction cost of that charging station.

The relative performances of the robust and deterministic schemes in each of the three simulations are compared based on the different measures (Table 2): (1) construction cost, (2) travelers' cost, (3) total cost, and (4) cost of travelers who charge their EVs at least once (referred to as *charging travelers*). Regarding construction cost, all instances of Simulations 1 and 2 are completely

Table 2. Performance of robust and deterministic schemes in Monte Carlo simulation for the Sioux Falls network

Simulation	Measures (costs are in million dollar unit)	Robust scheme	Deterministic scheme
1	Number of feasible instances	1,000	40
	Average travelers' cost	\$75,135	\$75,160
	Average charging travelers' cost	\$5,474	\$5,498
	Average total cost	\$75,140	\$75,165
	Standard deviation of travelers cost	145	146
2	Number of feasible instances	1,000	0
	Average travelers' cost	\$78,821	\$78,839
	Average charging travelers' cost	\$5,776	\$5,795
	Average total cost	\$78,826	\$78,845
	Standard deviation of travelers cost	119	120
3	Number of feasible instances	1,000	1,000
	Average travelers' cost	\$70,760	\$70,803
	Average charging travelers' cost	\$5,115	\$5,159
	Average total cost	\$70,765	\$70,806
	Standard deviation of travelers cost	101	102

Table 3. Relative performance of robust schemes with different construction budget cases in Monte Carlo simulation based on Budget class 1 in Sioux Falls

Simulation	Measures (costs are in million dollar unit)	Construction budget case		
		2	3	4
1	Relative construction cost	+\$3	+\$3	+\$2
	Relative travelers' cost	−\$14	−\$19	−\$23
	Relative penalty of unused capacities of charging stations	+\$0.16	+\$4.67	+\$4.97
	Relative charging travelers' cost	−\$22	−\$28	−\$31
	Relative total cost	−\$11	−\$16	−\$21
2	Relative construction cost	+\$3	+\$3	+\$2
	Relative travelers' cost	−\$19	−\$24	−\$28
	Relative penalty of unused capacities of charging stations	+\$0.21	+\$4.83	+\$5.14
	Relative charging travelers' cost	−\$27	−\$32	−\$36
	Relative total cost	−\$16	−\$21	−\$26
3	Relative construction cost	+\$3	+\$3	+\$2
	Relative travelers' cost	−\$12	−\$17	−\$20
	Relative penalty of unused capacities of charging stations	+\$0.12	+\$4.38	+\$4.68
	Relative charging travelers' cost	−\$18	−\$23	−\$27
	Relative total cost	−\$10	−\$15	−\$19

infeasible under the deterministic scheme as the charging demands are not satisfied based on the distributions in these simulations. Hence, the unplanned capacity expansions of charging stations are required under a deterministic scheme to address the high charging demand during the planning horizon, which can lead to tremendous costs in practice. This indicates the poor performance of the deterministic scheme under higher travel demands than anticipated in practice. Regarding travelers' costs, the robust scheme also reduces the average cost of travelers compared to the deterministic scheme in Simulations 1–3. Specifically, the robust scheme outperforms the deterministic scheme in terms of the average cost of travelers by \$25 million, \$18 million, and \$43 million over the course of 18 years of planning horizon in Simulations 1–3, respectively. The travelers' cost difference in Simulation 3 is higher compared to Simulations 1 and 2 due to the unplanned capacity expansion under the deterministic scheme. It provides more flexibility for travelers in their charging station selection process in Simulations 1 and 2. This results in lower travel cost differences under Simulations 1 and 2 compared to Simulation 3.

Besides, the standard deviation of the travelers' cost under a robust scheme is also less than or equal to that under the deterministic scheme in Simulations 1–3, which demonstrates the less volatile performance of the robust scheme compared to the deterministic scheme. This is due to the more conservative approach of the road infrastructure agency under the robust scheme to plan for the worst-case travel demand scenario. A similar discussion can be provided for the differences between robust and deterministic schemes in terms of average total cost and cost of charging travelers.

Next, we investigate the impact of the construction budget on the optimal design of electric charging infrastructure using four cases. The construction budget used in the previous analysis is referred to as Case 1, which is a base case in this analysis. The construction budget in each period for Cases 2–4 is derived by multiplying the construction budget of Case 1 by 1.5, 2, and 2.5 for each period, respectively. The relative performances of the robust scheme under different construction budgets in each of three simulations are compared based on budget Case 1 using different measures in Table 3 including (1) construction cost, (2) travelers' cost, (3) penalty of unused capacities of charging stations, (4) total cost, and (5) cost of charging travelers. Under budget Cases 2 and 3, the construction cost increases by \$3 million compared to Case 1 due to the higher number of constructed charging stations. However, it reduces by \$1 million under budget Case 4 compared to Cases 2 and 3, since it is possible to construct more charging stations in the initial periods with lower costs. Although there is a penalty for the unused capacities of charging stations, the number of constructed charging stations increases with the increase in the budget. This is because the decrease in the travelers' cost caused by constructing more charging stations prevails over the penalties caused by the unused capacities of the charging stations. For instance, in Simulation 1, the travelers' cost decreases by \$14 million in Case 2 while the penalty for unused capacities of charging stations is increased by \$160,000. As the construction budget increases, there is more construction in the initial periods of the planning horizon since the construction is less costly in those periods compared to the latter ones. Further, the average traveler's cost decreases by \$14 million, \$19 million, and \$12 million for Case 2 compared to Case 1, in Simulations 1–3, respectively. The decrease is smaller for Case 3 compared to Case 2, and also for Case 4 compared to Case 3. This shows that even though more charging stations are constructed in Cases 3 and 4 compared to Case 2, it does not result in a significant decrease in the average cost of travelers. This happens because the travelers are already choosing their desired charging stations along their paths, and hence, constructing more charging stations cannot help them further decrease their travel costs. A similar discussion can be provided for the differences between robust schemes with different budget cases in terms of average total cost and cost of charging travelers.

Concluding Remarks

This study investigated the optimal location of electric charging stations and the decommissioning of the existing refueling stations in the context of intercity trips. The uncertainties in refueling and electric charging demand are taken into account by considering uncertainties in travel demand forecasts over a long-term planning horizon. The uncertain forecasts of travel demand are taken into account using a travel demand uncertainty set in each period. Furthermore, due to the significant difference in driving ranges of various EV models, this study also accounts for the driving range heterogeneity of EVs.

The problem is formulated as a min-max mathematical program in which the weighted sum of the worst-case (maximum) total system travel cost and the total penalty for unused capacities of charging stations during the planning horizon is minimized. Since the formulated min-max problem is considered an NP-hard problem, a cutting-plane scheme is adopted to solve the problem efficiently, in which two subproblems are solved in each iteration. The first subproblem yields the optimal timeline and location for constructing new charging stations and decommissioning the existing refueling stations based on a subset of demand uncertainty sets. The second subproblem identifies a new worst-case travel demand uncertainty vector to include in the demand uncertainty subset of the first subproblem.

The problem is applied to the Sioux Falls network. It is assumed that for this network, the road infrastructure agency seeks to determine the optimal location and timeline for constructing new electric charging stations and decommissioning existing refueling stations. It is shown that due to the higher conservatism of the road infrastructure agency under the robust scheme, a higher number of charging stations needs to be constructed compared to the deterministic scheme. Further, under the robust scheme, new charging stations are located in more congested areas of the network, compared to the deterministic scheme. It is also observed that if the refueling demand is significantly lower than the operational capacity of refueling stations, there is no significant difference between the robust and deterministic scheme strategies for decommissioning the existing refueling stations.

Three sets of Monte Carlo simulations were carried out to assess the performance of a robust scheme compared to its deterministic counterpart. The results of the computational experiments illustrate that the proposed robust scheme outperforms the deterministic scheme based on various criteria such as travelers' cost, charging travelers' cost, construction cost, and total cost. In particular, while the deterministic scheme cannot satisfy any of the simulation instances generated based on the uniform and pessimistically asymmetric distributions, all the simulation instances are feasible under the proposed robust scheme. Further, the comparison of robust schemes with different classes of construction budget illustrates that although constructing more charging stations helps to decrease the travelers' costs, constructing too many charging stations, beyond a certain point, does not significantly decrease the travelers' costs.

The framework presented for constructing electric charging stations over a long-term planning horizon can provide guidance to road agencies in their long-term planning and budgeting functions. This is important in the current era in which these agencies continue to seek knowledge on how best they can prepare the existing roadway infrastructure to support a new era of transformative transportation technologies, including automated, connected, and electric vehicles. Such guidance can also help mitigate the inherent uncertainties associated with long-term planning with regard to these technologies. The level of service is always a function of supply and demand, and as stewards of the public road infrastructure, road agencies are responsible for anticipating demand and providing infrastructure supply. On the one hand, inadequate infrastructure will not only slow the adoption of the new technologies but also pose public relations problems for the agency. On the other hand, excess supply will lead to capacity underutilization, economic inefficiency, and the waste of scarce resources. The developed framework can also help road agencies prepare proactively for emerging technologies in a more confident manner. The framework can also be used by agencies to incorporate robustness into their long-term EV infrastructure plans to account for inevitable uncertainties associated with demand and supply. The framework presents (and demonstrates), for the benefit of road agencies, the advantage of robust planning over deterministic planning. Further, the framework is designed to be flexible to adjust to the road agency's future objectives, which often evolve with changes in the political environment, economic conditions, or social forces. The framework and solution method are designed to facilitate the practical implementation of various network topologies, the inventory of existing or required charging/refueling stations, and the length of the planning horizons.

This research can be extended in several directions. First, although our study considers the uncertainty in travel demand, the uncertainty in the market penetration of different classes of EVs has not been assessed. An interesting research direction is to investigate the market penetration rate of EVs as a stochastic function of charging station availability, electricity or gas prices, and potential government incentives. Second, the emergence of connected and autonomous vehicles (CAVs), which are expected to serve as EVs, can impose high levels of uncertainty on the charging behavior of EV-using travelers. Hence, another future research direction is to incorporate the charging behavior of CAVs into the robust design of charging stations. Third, as the present study focuses on intercity trips, the link travel times are assumed to be constant. Therefore, a future study could address intracity trips and take into account traffic congestion within the city.

Data Availability Statement

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

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Notation

The following symbols are used in this paper:

A = set of links;

$\check{A}$ = set of dummy links;

B^t = construction budget for charging stations in period t;

$c^t_{i,j}$ = delay for link (i,j) in period t;

$\hat{c}^{m,t}_{j,j'}$ = pseudodelay of dummy link (j,j') for class m in period t;

$E^{m,t}_{r,s}$ = set of travel demand uncertainty of each vehicle class m for each O-D pair (r,s) in period t;

$e^{w,m,t}_{ij}$ = binary variable that determines whether link (i,j) is a part of feasible path of travelers between O-D pair w for class m in period t;

$f^{w,t,m}_{i,j}$ = flow of vehicle class m travelers of O-D pair w between link (i,j) in period t;

H_1 = total system travel time;

H_2 = total penalty of unused charging stations capacities;

$\bar{h}_j$ = minimum acceptable refueling demand to maintain refueling station j;

$K^{m,t}_{r,s}$ = set of paths of each vehicle class m for each O-D pair (r,s) in each period t;

k_i^t = construction cost of charging station of node i at period t;
$L_{i,j}$ = length of link (i,j);
M = set of vehicle classes;
N = set of nodes;
$\bar{\bar{N}}$ = set of dummy nodes with existing refueling stations;
$\bar{N}$ = set of dummy candidate nodes for construction of charging stations;
$\check{N}$ = set of dummy nodes with existing charging stations;
n_j = charging/refueling capacity of charging/refueling station at node j;
$p_{r,s}^{m,e,t}$ = binary variable that indicates whether scenario e is realized for vehicle class m of O-D pair (r,s) in period t;
Q = travel demand uncertainty set;
$q_{r,s}^{m,e,t}$ = travel demand of vehicle class m of O-D pair (r,s) under scenario e in period t;
$q_{r,s}^{e,t}$ = aggregate travel demand of O-D pair (r,s) under scenario e in period t;
$q_{r,s}^{m,t}$ = realized travel demand of vehicle class m of O-D pair (r,s) in period t;
$R^{m,t}$ = driving range of class m vehicle in period t;
$u_i^{w,m,t}$ = traveler distance just before visiting node i from the last visited charging for travelers of O-D pair w for class m in period t;
$u_i^{\prime w,m,t}$ = traveler distance after visiting node i from the last visited charging for travelers of O-D pair w for class m in period t;
$\nu_{i,j}^t$ = traffic flow of link (i,j) in period t;
W = set of O-D pairs;
Υ_i = recharging or refueling amount at node i;
β^t = value of time of travelers in period t;
Γ^t = uncertainty budget in period t;
Δ^t = conversion factor to calculate the present value of cost of period t;
$\delta_{k,i,j,r,s}^{m,t}$ = path indicator which is equal to 1 if the link (i,j) in on path k for vehicle class m travelers of O-D pair (r,s) in period t;
$\zeta_{ij}^{w,t,m}$ = imposed excessive travel time between link (i,j) for travelers of class m between O-D pair w at period t;
θ_i^t = operation status of charging station at node i and period t;
κ = conversion factor for the costs of travelers and unused charging station capacity from hourly basis to the basis of each period duration;
Λ = sufficient large number;
$\mu_i^{w,t,m}$ = travel time of travelers of O-D pair w for class m at node i and in period t;
π = constant interest rate;
$\rho_{i,j}$ = auxiliary variable that equals to zero if link (i,j) belongs to the shortest path and unrestricted otherwise;
τ = set of periods;
ϕ_1 = weight of total system travel time;
ϕ_2 = weight of total penalty of unused chargers in the objective function;
χ_i = remaining charge or fuel level at node i after recharging or refueling, respectively;
Ψ = penalty for unused capacities of charging stations;
$\Omega(\boldsymbol{q})$ = UE link flows for each $\boldsymbol{q}$;
$\varrho_i^{m,t}$ = maximum refueling or recharging amount that can be provided at node i for vehicle class m in period t;
$\varsigma_{i,j}$ = binary variable that is equal to 1 if link (i,j) belongs to the shortest path, and 0 otherwise; and
φ_i^t = operation status of refueling station at node i. and period t.

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