Designing a Network of Electric Charging Stations to Mitigate Vehicle Emissions

Miralinaghi, M.; Correia , G.; Seilabi, S. E.; Labi, S.

DOI
10.1109/FISTS46898.2020.9264883

Publication date
2020

Document Version
Accepted author manuscript

Published in
2020 Forum on Integrated and Sustainable Transportation Systems (FISTS)

Citation (APA)
Miralinaghi, M., Correia , G., Seilabi, S. E., & Labi, S. (2020). Designing a Network of Electric Charging Stations to Mitigate Vehicle Emissions. In *2020 Forum on Integrated and Sustainable Transportation Systems (FISTS): November 3-5, 2020, Delft - The Netherlands* (pp. 95-100). [9264883] IEEE . https://doi.org/10.1109/FISTS46898.2020.9264883

Designing a Network of Electric Charging Stations to Mitigate Vehicle Emissions

Mohammad Miralinaghi, Gonçalo Homem de Almeida Correia, Sania E. Seilabi, Samuel Labi

Abstract— **Metropolitan authorities continue to seek programs and initiatives to reduce emissions in their jurisdictions. It has been shown that transitioning from fossil fuel to electric propulsion of transportation can help realize this goal. However, the current market penetration of electric vehicles (EVs) compared to internal combustion engine vehicles (ICEVs) remains very small. This paper proposes a framework to address this problem over a long-term analysis period. The paper accounts for consumers' vehicle-purchasing propensities and their route choices, locations of EV-charging and ICEV-refueling stations. In the proposed framework, new EV charging stations are provided at selected locations and/or existing gas stations are repurposed by the transport agency's decision-maker (through policy) in conjunction with the private sector (through investment). The paper presents a bi-level mathematical model to capture the decision-making processes of the transport agency and the travelers. Underlying the framework is a solid theoretical foundation for the EV charging network design. The design problem is solved using an active-set algorithm. The study results can serve as guidance for metropolitan transport agencies to establish specific locations and capacities for EV stations and thereby to contribute to long-term reduction of emissions.**

Keywords: Network design, Charging stations, Electric vehicles, Diffusion model.

I. INTRODUCTION

One of the key initiatives in the 2017 Paris Agreement was the reduction of greenhouse gas (GHG) emissions, a primary contributor to climate change [1] and a continuing subject of worldwide mitigation efforts. It has been established that the second largest source of GHG emissions is passenger and freight transportation [2]. This is because the dominant means of vehicle propulsion, the internal combustion engine vehicles (ICEVs) continue to use fossil fuels as their energy source [3]. In Europe, legislative efforts to support GHG emissions reduction has occurred through national pledges to end ICEV sales by 2040 so that the Paris Agreement target emissions can be achieved [4]. Notwithstanding these initiatives, the adoption of EVs continue to face formidable obstacles. The biggest barrier is the inadequacy of electric charging infrastructure. For example, in the US, there exists only 16,000 public EV charging stations; this is rather miniscule in comparison to the inventory of existing gas stations [5].

Against this background, this paper provides a framework to establish the optimal locations of electric charging facilities on an urban road network to serve electric vehicles. The approach recognizes that static charging of a parked vehicle via cable, is the most common mode of charging. Then, of the various levels of this mode, the third level, namely, DC fast charging using commercial grade 480-volt AC power service with at least 20 minutes recharge time [6] is what is considered in the framework.

This is a variant of the classic facility location problem (FLP) that has been studied widely. The literature on EV charging stations can be placed in two categories: (a) those that assume link travel times are constant [7], [8] and are more appropriate for intercity trip contexts where the travelers' route decisions do not significantly impact their travel times. (b) those which assume that link travel times are a function of link flows, and therefore consider the congestion effects and travelers' route choices [9], [10]. This second category of studies are more relevant in the context of intracity trips where congestion influences the travelers' route decisions. The context of this paper is more consistent with that of the second category because in the paper, we seek to provide optimal locations for EV charging stations while considering traffic congestion. It should be noted, however, that this paper's framework can be applied to the first category by simply eliminating the component that addresses congestion effects by assuming constant travel times.

It is expected that this paper's framework can help increase EV adoption. Ultimately, a higher EV market share can help metropolitan agencies realize reduced vehicle emissions and thereby promote environmentally sustainable transportation. In the context of vehicle fuel, the goal is to gradually change gas stations to EV charging stations. Generally, the private sector constructs and operates gas stations and largely, EV charging stations, Governments can provide incentives for the private sector regarding EV charging station investments. Over the ICEV-EV transition phase, the expectation is that there will be stations that serve both ICEVs and EVs at the same location. Through policy, the transition must be smooth because any abrupt change (sudden conversion of all gas stations to EV charging

*Research is supported by Center for Connected and Automated Transportation, U.S. Department of Transportation.

Mohammad Miralinaghi is with the Center for Connected and Autonomous Transportation at Purdue University, West Lafayette, IN 47906 USA (corresponding author, phone: +1 (765) 494 5926; e-mail: smiralin@purdue.edu).

Gonçalo Homem de Almeida Correia was with Department of Transport and Planning at Delft University of Technology, Delft, P.O. Box 5048 77005 The Netherlands. (e-mail: G.Correia@tudelft.nl).

Sania E. Seilabi is with the Center for Connected and Autonomous Transportation at Purdue University, West Lafayette, IN 47906 USA (e-mail: sesmaei@purdue.edu).

Samuel Labi is with the Center for Connected and Autonomous Transportation at Purdue University, West Lafayette, IN 47906 USA (e-mail: labi@purdue.edu).

stations) will leave ICEV consumers unable to refuel. On the other hand, a tardy rate of EV charging station provision compared to EV adoption, will leave EV users with inadequate charging stations, and ultimately, poor level of service, and frustration, and therefore will discourage EV use. In this paper therefore, we recognize that the framework for designing an EV charging network should be able to translate the specific impact of charging infrastructure availability on EV market adoption over the planning horizon. In addition, the framework should address not only the long-term charging needs of a prospectively growing EV fleet, but also the long-term refueling needs of ICEV consumers.

The optimization framework has an inherently bi-level structure. The bi-level framework has been in different contexts of transportation system problems[11]–[17]. At the upper level, the decision-maker is the transport agency who seeks to minimize the total system vehicle emissions by adopting policies that lead to the development (via private sector investment) of optimal locations of EV charging stations and the replacement of existing gas stations, over the planning horizon. The transport decision-maker also decides the optimal capacity of the charging station at each location, in each period. These planning-level decisions are subject to budget constraints in each period, and it is assumed that the budget does not carry over to the next period. At the lower level, travelers aim to minimize their travel times by making route and vehicle type choices based on the decisions made by the agency at the upper level. It is assumed that the ICEV travelers stop once to refuel during their trips and that the EV traveler route choices are subject to the constraint posed by the driving range (how long or far the electric charge will last). In the context of intracity trips, the effect of the EV driving range has been recognized duly in a number of past studies [10], [18]. Driving range limitations may arise not only from current battery technology but also from the needs of the travelers. For example, travelers may lack charging ports at their residences. Even where they do, they may forget to charge their vehicles and will therefore need to charge en route. It is assumed that EV travelers have a higher cost (due to the higher purchase cost) compared to ICEVs. It can be expected that over the planning horizon, this additional cost will decrease due to technological advancement. The paper applies a diffusion model to predict EV market share and to model travelers' vehicle type choices.

We consider two types of vehicle propulsion in this paper: EVs and ICEVs. Other propulsion types, such as hydrogen fuel and plug-in hybrid vehicles, are not considered. With regard to the transition, ideally, it should occur over a planning horizon of adequate length to provide a smooth transition for travelers. For this reason, is useful for the transport agency decision-maker to adopt a multi-year planning horizon and to divide this horizon into multiple periods, and to derive the optimal number, locations and operational capacities of EV charging stations during each period. In addition, the paper assumes that a certain percentage of ICEVs needs to refuel en route, and this percentage is assumed to be constant within a period but varying across periods. The paper does not consider emissions from power plants that produce electricity for EV charging stations.

The remainder of this paper is organized as follows. The next section introduces some preliminaries and then, the bi-level model is formulated. This is followed by the discussion of results and insights obtained from numerical experiments. Finally, some concluding remarks are presented.

II. Notations

The planning horizon is divided into T periods each of multiple years' duration. Two vehicle types are considered: ICEVs and EVs. ICEVs are further classified into two classes based on their refueling needs. Let $G = (N, A)$ represent the road network where N and A represent the set of nodes and links, respectively. Let W and S denote the set of O-D pairs and origins, respectively. Let s and r denote the origin and destination of O-D pair w. The set of nodes N consists of three types of nodes, (i) $\hat{N}$ candidate nodes for EV charging stations, (ii) $\overline{N}$ nodes with existing refueling stations and (iii) other nodes $\overline{\overline{N}}$. It is assumed that nodes with existing refueling stations are also candidates for charging stations ($\overline{N} \subseteq \hat{N}$) with fixed flow capacity f_i^t to serve both EVs and ICEVs. Let $v_{ij}^{w,t,m}$ and v_{ij}^t denote the flow of user class m of O-D pair w and aggeregate flow of link (i, j) in period t, respectively. The travel time of link (i, j), σ_{ij}^t, follows the Bureau of Public Roads (BPR) function:

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

where θ_{ij}^t and χ_{ij}^t denote the free-flow travel time and capacity of link (i, j) in period t, respectively.

III. Study Methodology

We formulate the problem as a bi-level program. In the upper-level, the transport decision-maker seeks to minimize vehicle emissions. The transport agency decision-maker (whose policy influences the private-sector investor) has the following decision variables: the EV charging station locations and operating capacities. These upper-level decisions are subject to budget constraints at each period of the planning horizon. It is ensured that the electric charging and refueling stations capacities are sufficient to address the travelers' needs within each period. At the lower level, travelers seek to fulfill their travel needs while minimizing their travel costs. The travelers' decision variables are to choose the route and vehicle type (EV vs. ICEV). In sum, the transport decision-maker promotes the construction of EV charging stations or re-purposing existing gas refueling stations into EV charging stations, and the ICEV and EV travelers respond by purchasing EVs and changing their routes to reduce their travel times on trips that involve refueling/recharging. It should be noted that these outcomes impact the travel times of travelers that have no need for refueling/recharging. At conditions of user equilibrium, travelers are unable to further reduce their travel times by unilaterally changing their routes. For this reason, the route and vehicle type decisions of ICEV/EV travelers will depend on their travel times and refueling/recharging needs. That means that the routes selected by the travelers need to be consistent with the specified EV-driving range or must contain nodes where ICEV refueling stations are located.

A. Modeling the Agency's Decisions at the Upper-Level

The upper-level model addresses the decisions of the transport agency decision-maker who seeks to minimize vehicle emissions by providing (through policy that promotes private-sector investment), EV charging stations at optimal locations and operating levels, over a long planning horizon. In this paper, we use carbon monoxide (CO) as the indicator of vehicle emissions, for two reasons [19], [20]: (a) vehicles are the main source of CO emissions. (b) the emissions of other pollutants such as carbon dioxide share similarity with that of CO. For link (i,j), the function for CO emissions $Y_{ij}^t(v_{ij}^t)$ (in g/veh) in period t is [19]:

$$Y_{ij}^t(v_{ij}^t) = 0.2038\sigma_{ij}^t(v_{ij}^t)\cdot\exp\left(\frac{0.7962L_{ij}^t}{\sigma_{ij}^t(v_{ij}^t)}\right) \qquad \forall(i,j),t \tag{2}$$

Where: L_{ij}^t is the link length (i,j) (in km) in period t. σ_{ij}^t is the travel time (mins) on link (i,j). ICEVs are the only source of CO emissions because the traffic stream consists of only EVs and ICEVs. The rate of the road network vehicle emissions is: $\sum_t\sum_{(i,j)\in A}\sum_{m<3} v_{ij}^{w,t,m}Y_{ij}^t(v_{ij}^t)$ per hour, through the planning horizon.

Let $y_i^{k,t}$ equal to 1 if node i's EV charging station operates at level k in period t and, 0 otherwise. Further, through policy and resulting private-sector investment, the transport agency decision-maker can cause reduction in the number of gas stations and their eventual conversion to EV charging stations. Let φ_i^t be equal to 1 if node i's gas station operates in period t and, 0 otherwise. Let $\zeta_i^{t,2}$ and $\zeta_i^{t,3}$denote the refueling flow of ICEVs and charging flows of EVs through station located at node i in period t.

The upper-level model, which is subject to budget constraints where a budget B^t is pre-specified for each period t, can be formulated as follows:

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

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

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

$$\varphi_i^t \le M\cdot\zeta_i^{t,2} \qquad \forall t,\forall i\in\bar{N} \tag{6}$$

The objective (3) minimizes the total vehicle emissions rate during the planning horizon. Constraint (4) restricts the total construction cost of EV charging stations from exceeding the budget in the first period. Constraints (5) ensure that the EV charging station construction cost of does not exceed the budget in period t. This states that if an EV charging station does not exist at node i in period $(t-1)$ of level k ($y_i^{k,t}=0$), then there is a need to invest c_i^k in period t to construct one at that location. On the other hand, if the EV charging station of node i exists in period $(t-1)$ ($y_i^{k,t}=1$), then no cost is assigned. Constraints (6) state that if ICEVs do not use refueling station of node i in period t, it can be closed in that time period and remain closed for the rest of the planning horizon.

B. Modeling Travel Decisions at the Lower-Level

In response to the policies and actions of the transport agency decision-maker and the private-sector investor, respectively, in the upper level, the travelers at the lower level make decisions related to the mode and route choices of travelers, and EV adoption. The paper applies the diffusion model concept to estimate the travel demand $d^{w,t,3}$ of EVs between each O-D pair w in time period t. In the diffusion model, the EV adoption rate in each period depends on the adoption rate and the net benefit gained by the EV in the previous period. Diffusion models are widely used in the literature to model the adoption rate of new products such as automated vehicle technology [9].

The paper accommodates the driving-range capability of EVs, by modifying the single-period constraints proposed by Zheng et al. [10] to yield a multi-period setting. The multi-class traffic assignment subject to the decisions of the transport decision-maker and private-sector investor at the upper level, is formulated. The traffic assignment needs to satisfy the range limitations of the EVs and refueling stop of ICEVs. This implies that the equilibrium condition can be achieved using a feasible subnetwork defined by $e_{ij}^{w,t,m}$. Therefore, the traffic assignment problem at the lower level can be formulated as follows:

$$\min Z^L = \sum_{(i,j)\in A}\int_0^{v_{ij}^t}\sigma_{ij}^t(\omega)d\omega \tag{7}$$

$$\sum_{(w,m)} v_{ij}^{w,t,m} = v_{ij}^t \qquad \forall(i,j),t \tag{8}$$

$$\sum_{j:(j,i)\in A} v_{ji}^{w,t,m} - \sum_{j:(i,j)\in A} v_{ij}^{w,t,m} = q_i^{w,t,m} \qquad \forall w,i,t,m \tag{9}$$

$$v_{ij}^{w,t,m} \le M\cdot e_{ij}^{w,t,m} \qquad \forall(i,j),w,t,m>1 \tag{10}$$

$$v_{ij}^{w,t,m} \ge 0 \qquad \forall(i,j),w,t,m \tag{11}$$

where $q_i^{w,t,m}$ denote the travel demand of O-D pair w originated from node i of vehicle type m in period t. Equations (7) – (11) represent the conventional static traffic assignment model with additional constraints (10) which state that user classes 2 and 3 can only use their corresponding feasible subnetworks. The bi-level model ((3) – (11)) includes both upper- and lower-level models which can be solved using commercial solvers. However, this mathematical program with equilibrium constraint (MPEC) includes both mixed-integer and complementarity constraints which renders it rather difficult to solve. We adopt the active-set algorithms [21] to solve the MPEC bi-level model ((3) - (11)).

IV. CASE STUDY

We use a case study to carry out computational experiments that demonstrate the applicability of the proposed model. The case study area is the Sioux-Falls network which possesses 24 nodes and 76 links. We use the settings proposed by Zheng et al. [10] that has: 72 O-D pairs for this network, where the number of origins is limited to 3 (nodes 1,2 and 3), and we assume a travel demand growth of 5% through the planning horizon. The planning horizon is divided into five periods. The candidate nodes for locating an EV charging station are shown in orange and yellow (Fig. 1). The existing refueling stations are located at nodes 4, 10, 12, 14, 18, 20 and 22. Consistent with recent studies. the EV driving range is assumed to be 12 miles [22].

Two operating levels are considered for each charging station. The capacity of the first level p_i^1 is 300 vehicles per hour with construction cost c_i^1 equal to $100,000. The capacity of the second level p_i^2 is 400 vehicles per hour with construction cost c_i^2 equal to $200,000. For nodes 16 and 17, the construction costs for operating levels 1 and 2 are equal to $200,000 and $400,000 because it is necessary to build new stations at these nodes due to the lack of existing gas stations at these nodes. The fixed-flow capacity f_i^t of a refueling station to serve both EVs and ICEVs is equal to 600 vehicles per hour. Without constructing the EV charging stations and promoting EVs, the total emissions rate under user equilibrium condition is equal to 432.52 kg/hr through the planning horizon.

In the analysis, we assume that the initial market share of EVs is 5% and a potential market share of 75%. The value of time of the drivers is assumed to be 20 $/hr. Further, it is assumed that 15% of the ICEV cars need to refuel in each hour. The optimization results are obtained using GAMS [23] on one cluster node with four 2.3-GHz 12-core AMD Opteron 6176 processors and 192 GB RAM per node. Note that the parameter values that are used in this section are primarily for illustrative purposes and for testing the model.

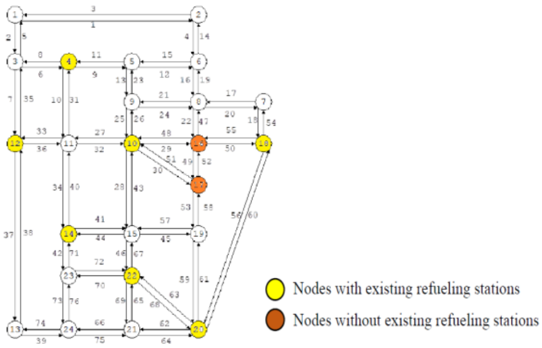


Fig. 1. Sioux-Falls network with candidate charging station locations.

The impact of driving range on the market penetration of EVs and vehicle emissions rate is investigated. It is assumed that through the transport agency decision-maker's policies and private sector investment, $100,000 is allocated in each period for constructing EV charging stations. Three driving-range scenarios: 12 miles (scenario 1), 15 miles (scenario 2) and 20 miles (scenario 3), are considered. Fig. 2 illustrate the impact of EV driving range on the spatial distribution of EV charging station locations and EV market penetration rates, respectively.

For the driving ranges 1, 2 and 3, the vehicle emissions rates are 232.37 kg/hr, 217.41 kg/hr and 210.55 kg/hr, respectively. It is interesting to observe from the results that that for driving range 3, fewer EV charging stations are constructed, compared to driving ranges 1 and 2. Compared to the vehicle emissions rate under budget scenario 2 (209.636 kg/hr), it is clear that with technological advancement of EVs which results in higher driving range, there is a reduction in the need for charging stations. Further, because the need for recharging is reduced with increasing driving range, travelers can fulfill their travel needs without deviating from their optimal routes just so they can recharge their vehicles. In addition, in the case study network, nodes 16 and 17 are not selected for installing EV charging stations due to higher construction costs compared to other nodes that have existing gas (refueling) stations.

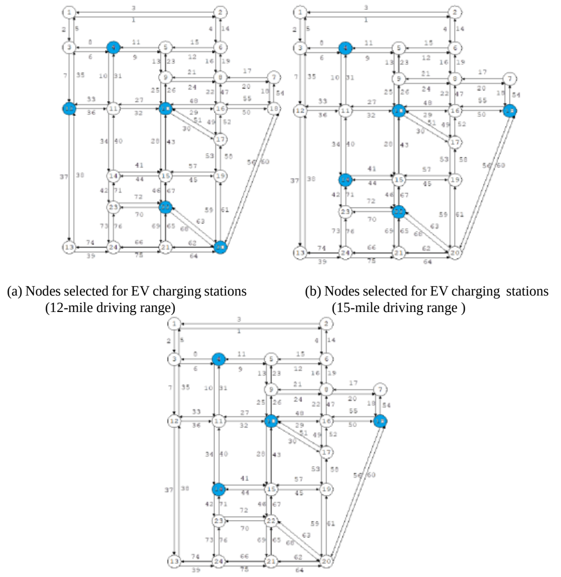
V. Conclusion

We present in this paper, an approach for scheduling the deployment of EV charging stations within a long-term planning horizon and a specified budget with the goal of minimizing urban vehicle emissions. We achieve this goal by identifying optimal locations for constructing new EV charging stations and repurposing the existing gas stations. The transport decision-maker's planning horizon is divided into multiple periods. Through agency policy (and private sector initiatives fostered by the agency policy), a budget is allocated for charging station construction within each period. This motivates travelers to gradually shift from ICEVs to EVs, and therefore provides a smoother transition from refueling stations to EV charging stations. The optimization problem is formulated as a bi-level model. At the upper level, the transport agency decision-maker and the private sector make the optimal decision regarding the number, locations, and capacities of the needed EV charging stations. Based on the decisions made at the upper level, travelers (at the lower level) decide on their choices of route and vehicle type (EV vs. ICEV). To capture the travelers' mode choices, the paper applied the diffusion model which accounts for the influence of the net benefit earned by EV travelers in the previous period, on the EV market penetration in the subsequent period. The bi-level model is solved using an active-set algorithm.

The numerical experiments demonstrate that with the technological advancements and evolution of the EV driving range, transport decision-makers will need to invest progressively lower amounts of funds to satisfy the needs of travelers in the charging network. The results showed that for a higher driving range, there is a significant reduction in the need for charging stations. Also, because the need for recharging is reduced with increasing driving range, travelers can fulfill their travel needs without deviating from their optimal routes just so they can recharge their vehicles.

This research can be extended in several directions. First, this paper only considers ICEVs and EVs. However, plug-in hybrid vehicles (PHEVs) can both recharge at EV charging stations and refuel in gas stations. Hence, they can play an important role in this transition phase toward adopting EVs and hence, it is vital to consider them in the proposed framework. Second, this paper assumes zero delay for charging and refueling of EVs and ICEVs, respectively.

However, this assumption needs to be relaxed in future studies as the charging delay of EVs currently is significantly higher compared to the ICEVs' refueling delay. This can affect the decision of travelers regarding their route and vehicle type choices.



(a) Nodes selected for EV charging stations (12-mile driving range)

(b) Nodes selected for EV charging stations (15-mile driving range)

(c) Nodes selected for electric stations (20-mile driving range)

Fig. 2. Selected nodes under different driving range scenarios.

REFERENCES

[1] IPCC, "Climate Change: Working Group III: Mitigation of Climate Change," 2007.

[2] H. M. A. Aziz, S. V. Ukkusuri, and X. Zhan, "Determining the Impact of Personal Mobility Carbon Allowance Schemes in Transportation Networks," *Networks Spat. Econ.*, vol. 17, no. 2, pp. 505–545, Jun. 2017.

[3] The Committee on Climate Change, "Fourth Carbon Budget Review – technical report," London, UK, 2013.

[4] K. Racherla and M. Waight, "Addressing EMI in Electric Cars with Radio Tuner Architecture [Future Directions]," *IEEE Consum. Electron. Mag.*, vol. 7, no. 1, pp. 15–124, Jan. 2018.

[5] J. Le Sage, "Electric vehicle charging points to rise significantly in 2018," *USA Today*, Dec-2017.

[6] D. Kettles, "Electric Vehicle Charging Technology Analysis And Standards," Cocoa, FL, 2015.

[7] Y. Huang, S. Li, and Z. S. Qian, "Optimal Deployment of Alternative Fueling Stations on Transportation Networks Considering Deviation Paths," *Networks Spat. Econ.*, vol. 15, no. 1, pp. 183–204, Feb. 2015.

[8] D. Wu, Y. Yin, S. Lawphongpanich, and H. Yang, "Design of more equitable congestion pricing and tradable credit schemes for multimodal transportation networks," *Transp. Res. Part B Methodol.*, vol. 46, no. 9, pp. 1273–1287, 2012.

[9] Z. Chen, F. He, and Y. Yin, "Optimal deployment of charging lanes for electric vehicles in transportation networks," *Transp. Res. Part B Methodol.*, vol. 91, pp. 344–365, Sep. 2016.

[10] H. Zheng, X. He, Y. Li, and S. Peeta, "Traffic Equilibrium and Charging Facility Locations for Electric Vehicles," *Networks Spat. Econ.*, vol. 17, no. 2, pp. 435–457, Jun. 2017.

[11] M. Miralinaghi, S. E. Seilabi, S. Chen, Y. T. Hsu, and S. Labi, "Optimizing the selection and scheduling of multi-class projects using a Stackelberg framework," *Eur. J. Oper. Res.*, vol. 286, no. 2, pp. 508–522, 2020.

[12] M. Miralinaghi, W. Woldemariam, D. M. Abraham, S. Chen, S. Labi, and Z. Chen, "Network-level Scheduling of Road Construction Projects Considering User and Business Impacts," *Comput. Civ. Infrastruct. Eng.*, pp. 1–18, 2020.

[13] L. Gong and W. Fan, "Optimizing Scheduling of Long-term Highway Work Zone Projects," *Int. J. Transp. Sci. Technol.*, vol. 5, no. 1, pp. 17–27, 2016.

[14] S.-M. Hosseininasab, S.-N. Shetab-Boushehri, S. R. Hejazi, and H. Karimi, "A Multi-objective Integrated Model for Selecting, Scheduling, and Budgeting Road Construction Projects," *Eur. J. Oper. Res.*, vol. 271, no. 1, pp. 262–277, Nov. 2018.

[15] S.-M. Hosseininasab and S.-N. Shetab-Boushehri, "Integration of Selecting and Scheduling Urban Road Construction Projects as a Time-dependent Discrete Network Design Problem," *Eur. J. Oper. Res.*, vol. 246, no. 3, pp. 762–771, 2015.

[16] M. Miralinaghi, S. E. Seilabi, S. Chen, Y.-T. Hsu, and S. Labi, "Time-Dependent Traffic Network Design with Multi-Class Projects," *Transp. Res. Board 98th Annu. Meet.*, no. 19–03832, 2019.

[17] M. Miralinaghi, Y. Lou, B. B. Keskin, A. Zarrinmehr, and R. Shabanpour, "Refueling station location problem with traffic deviation considering route choice and demand uncertainty," *Int. J. Hydrogen Energy*, vol. 42, no. 5, pp. 3335–3351, 2017.

[18] H. Liu and D. Z. W. Wang, "Locating multiple types of charging facilities for battery electric vehicles," *Transp. Res. Part B Methodol.*, vol. 103, pp. 30–55, Sep. 2017.

[19] Y. Yin and S. Lawphongpanich, "Internalizing emission externality on road networks," *Transp. Res. Part D Transp. Environ.*, vol. 11, no. 4, pp. 292–301,

Jul. 2006.

[20] H. M. A. Aziz and S. V. Ukkusuri, “Tradable emissions credits for personal travel: a market-based approach to achieve air quality standards,” *Int. J. Adv. Eng. Sci. Appl. Math.*, vol. 5, no. 2–3, pp. 145–157, Sep. 2013.

[21] L. Zhang, S. Lawphongpanich, and Y. Yin, “An active-set algorithm for discrete network design problems,” in *Transportation and Traffic Theory 2009: Golden Jubilee*, H. K. L. William, S. C. Wong, and K. Lo Hong, Eds. New York: Springer, 2009, pp. 283–300.

[22] C. Xie and N. Jiang, “Relay Requirement and Traffic Assignment of Electric Vehicles,” *Comput. Civ. Infrastruct. Eng.*, vol. 31, no. 8, pp. 580–598, Aug. 2016.

[23] R. E. Rosenthal, *GAMS — A User’s Guide*. Washington, DC.: GAMS Development Corporation, 2015.