INTERNATIONAL JOURNAL OF HYDROGEN ENERGY 42 (2017) 3335–3351

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/he

Refueling station location problem with traffic deviation considering route choice and demand uncertainty

Mohammad Miralinaghi [a,*], *Yingyan Lou* [b], *Burcu B. Keskin* [c,1], *Amirali Zarrinmehr* [d], *Ramin Shabanpour* [e]

[a] *School of Civil Engineering, Purdue University, W. Lafayette, IN 47907, USA*
[b] *Department of Civil, Environmental and Sustainable Engineering, Arizona State University, Tempe, AZ 85281, USA*
[c] *Department of Information Systems, Statistics, and Management Science, University of Alabama, Tuscaloosa, AL 35487, USA*
[d] *Department of Civil and Environmental Engineering, Tarbiat Modares University, Tehran, Iran*
[e] *Department of Civil and Materials Engineering, University of Illinois at Chicago, Chicago, IL, USA*

ARTICLE INFO

Article history:
Received 17 February 2016
Received in revised form
28 December 2016
Accepted 30 December 2016
Available online 18 January 2017

Keywords:
Refueling stations
Network design
Demand uncertainty
Robust optimization
Route choice

ABSTRACT

Construction of refueling stations in a traffic network is a major step toward the promotion of hydrogen fuel vehicles in the metropolitan areas. This research provides a framework for the refueling demand uncertainty and the effect of travelers' deviation to refuel considerations in the network. First, considering the refueling demand uncertainty of the hydrogen fuel vehicles market, we propose a discrete, robust optimization model in which refueling demand is formulated as an uncertainty set during planning horizon. A cutting plane algorithm is adopted to solve this robust centralized planning model. Numerical results demonstrate that the robust model can lead to more reliable design compared to the nominal plan. Second, a link-based bi-level program is proposed in which the lower level problem describes the user equilibrium traffic condition characterized by the locations of refueling stations. This model is solved using a computationally efficient genetic algorithm. Numerical examples indicate that as the refueling demand share increases, total system travel time, for both refueling and non-refueling users, increases. This increase is more pronounced in low levels of refueling demand share compared to high levels.

Introduction

Fossil fuels are broadly used in the modern industry and transportation systems. Limited oil resources and the global trend of increasing annual consumption have motivated the quest to approach healthier fuels [1]. Studies have foreseen the exhaustion of major fuel resources around the end of this century; for example, Ghorashi and Rahimi [2] indicated that oil and natural gas reserves in Iran, one of the primary

* *Corresponding author.*
E-mail address: miralinaghi@purdue.edu (M. Miralinaghi).
[1] Dr. Keskin's research is supported by TUBITAK 2221 program.
http://dx.doi.org/10.1016/j.ijhydene.2016.12.137
0360-3199/

exporters of natural resources, will end in the next 84 and 166 years, respectively. Further, global warming, as a controversial issue during the last decade, is consequence of concentrations of greenhouse gases produced by human activities such as consumption of fossil fuels in transportation sector. Studies show that a large share of global emission, approximately 27% in 2013, is caused by a transportation sector [3]. Researchers proposed several strategies to manage the transportation-related emissions in metropolitan area such as market-based instruments [4–6], intelligent transportation systems [7], and promoting alternative fuel vehicles (AFV) [8] to reduce reliance of transportation sector on fossil fuels.

As travelers become more sensitive about environmental sustainability, demand for renewable energy resources in transportation industry is increasing rapidly, leading to the growing concern for the development of AFV markets. Defined as vehicles that do not rely solely on “traditional” petroleum fuels, AFVs may broadly include the vehicles powered by flexible fuel, dual fuel, and electricity (hybrid or otherwise) [9,10]. According to United States Energy Information Administration [11], the number of AFVs in use in the United States has been increasing from 250,000 in 1995 to 1,250,000 in 2011. The International Energy Agency [12] reported that renewable energy would be capable of serving 7% of transportation fuels for the entire world in 2030. However, indicated in the alternative fuel literature and survey conducted by three groups of US National Renewable Energy Laboratory scientists and local coordinators of US Department of Energy Clean Cities Coalitions, the lack of refueling stations is recognized as the biggest barrier against the development of AFVs [13]. As the share of AFVs in the United States is increasing [11], the problem of locating alternative fuel stations should receive more attention in order to develop a transportation infrastructure that supports the growth of AFVs.

Different types of fuels are used by AFVs, e.g. natural gas [14,15], ethanol, electricity and hydrogen, which characterize their driving ranges and thereby define unique refueling needs for each type of them. While seeking to propose generalized formulation for the location problem of AFV refueling stations, in this study we focus on the AFVs using hydrogen fuel which is an alternative with great potential, as it can be used in both fuel cells and internal combustion engines (ICE) [16]. Construction of hydrogen refueling stations provides an appealing infrastructure to promote the hydrogen fuel vehicles. Currently, there are only 12 hydrogen refueling stations existing in the United States [17]. However, the projected number of hydrogen refueling stations increases to 68 stations by 2019 based on the California Fuel Cell Partnership roadmap [18]. In this stream of worldwide effort, Japanese government proposed to construct 100 hydrogen refueling stations by 2025 [19] while Europeans plan to commercialize 16 million hydrogen fuel vehicles by 2030 [20].

By promoting hydrogen fuel vehicles to substitute for gasoline vehicles, it can reduce the petroleum-based energy requirements by 42%. As the primary emission of hydrogen fuel vehicles is water, it can also reduce greenhouse gas emission by over 80% [21]. The state-of-the-art technology of the hydrogen fuel cell allows for a longer driving range (approximately 300 miles) and requires a comparatively shorter refueling time than other types of AFVs (averagely 4–7 min), thereby making hydrogen fuel vehicles comparable to its gasoline counterparts. Based on this feature, driving range of AFVs may not be the constraint for daily commutes within a city, while it can shift research focus to the determination of refueling station locations in limited urban space, considering intra-city commuter behavior [22].

A location problem of fueling stations generally involves the consideration of construction cost and service coverage of each station, which applies for refueling stations for AFVs as well. Herein, service coverage can imply the accessibility of refueling stations for AFV drivers and thereby affects their willingness of using AFVs. In other words, it also implies that driver's perspectives should be another important factor for determining the locations of AFV refueling stations; nevertheless, the perspectives of the demand side have not been fully explored in the literature. This study, focusing on the location problem of AFV refueling stations for hydrogen fuel vehicles, seeks to incorporate demand-side consideration into the problem by factoring the characteristics of intra-city trips. More specifically, two major demand-side issues that can affect the development of an AFV market and need to be reflected in the determination of refueling stations for hydrogen fuel vehicles are addressed in this research:

(i) Demand uncertainty: As the technology of hydrogen fuel vehicles and other AFVs is continuously evolving, the prediction of their market penetrations is inevitably subject to unknown/unexpectable future variations and demand-side responses [23,24]. Such uncertainty involved in the prediction of AFV market development has to be considered in the deployment of the associated refueling stations; otherwise, it may result in an inefficient resource allocation and thereby the predicament of market development.

(ii) Driver route choice behavior: The need for refueling may request a driver to deviate from his/her original route to travel to a refueling station. This deviation can be influential, particularly for an AFV market, where the provision of refueling stations is generally limited. If the deviation leads to a considerable increase of travel time, the willingness of using an AFV may significantly reduce as well. Hence, this study includes the consideration of driver route choice behavior upon the potential deviation for refueling in the location problem and formulates the behavior using a User Equilibrium (UE) framework for network traffic, so as to capture the demand-side responses to the location of AFV refueling stations.

This research proposes two models to accommodate these two issues respectively, which both consider the locations of refueling stations as the decisions made by a central planner – Robust Centralized Planning Model (RCPM) that formulates a refueling station location problem with demand uncertainty and Bi-Level Centralized Planning Model (BLCPM) where the UE-based flow allocation rules are incorporated in a network design problem featuring the locations of AFV refueling stations. To incorporate the UE route choice of travelers, traffic assignment model is used in lower level. Miralinaghi et al. [25,26] provide a comprehensive literature review on traffic assignment models. In contrast to the current literature, the two proposed models collectively account for ***robustness*** and ***behavioral*** realism in strategically deploying refueling stations for fostering the AFV market (by meeting market's needs). Since the driving range of hydrogen fuel vehicles is not a concern in intra-city trips, it is assumed that travelers only make one stop to refuel during their trips.

The remainder of the paper is organized as follows. The next section surveys the relevant literature and further identifies the research gaps. In Section Robust Centralized Planning Model (RCPM), RCPM formulation is presented. Section Bi-Level Centralized Planning Model (BLCPM) formulates the BLCPM as a mathematical program with complementarity constraints. The problem complexity is discussed and then, the model is solved by developing a genetic algorithm where the traffic assignment sub-model is tackled using complementarity assignment algorithm. Numerical examples are provided for each model within each section. Finally, Section Conclusions concludes the paper and highlights the contributions of this research.

Literature review

Current literature on the refueling station location problem

In the context of transportation planning, the location problem of fuel stations can be considered as a network design problem (NDP) in terms of determining the supply of relevant facilities. For the supply of alternative fuels, most existing published studies addressed the problem by maximum covering or set covering approaches. The former approaches aim to maximize the coverage of neighborhood arcs of the refueling stations, but demand and traffic flow patterns are not explicitly considered (e.g. Refs. [27,28]). The latter approaches are particularly popular in recent years and extended for a wide range of variations, mostly employing flow-based formulations (e.g. Refs. [29–32]). These studies generally sought to minimize the total cost of deployment while covering refueling demand, and computational efficiency was of great concern and dealt with.

To reflect the consideration of refueling needs, Wang and Lin [33] formulated the refueling station location problem as a set covering mixed integer program (MIP) where travelers are able to refuel along their paths based on their ranges. Wang and Wang [34] extended the model by adding the constraint of nodal demand coverage and restricting the stations to be within reasonable distances to all the nodes in the traffic network. Kim and Kuby [35] addressed this problem by focusing on the deviation of travelers from their original shortest paths due to refueling. They built a maximum covering formulation with the objective of maximizing the total covered refueling demand. They assumed that the desire of travelers for refueling at a particular station decreases with the increase of the deviation from their original shortest paths. Huang et al. [36] further relaxed the commonly used assumption that travelers only take the shortest paths but allowed multiple possible deviation paths between each origin-destination (O-D) pair. Lee et al. [37] proposed a location problem of charging stations for electrical vehicles (EV) based on user equilibrium assignment, from the perspective to avoid congestion induced by inappropriate station locations. Charging behavior of travelers is accounted for by assuming a remaining fuel range at each origin node follows a probabilistic distribution. With respect to the location problem of hydrogen refueling stations, Kang and Recker [20] incorporated a household activity pattern problem (HAPP) for trip scheduling and routing. The combined problem showed the importance of characterizing home-based trips/activities.

Research gaps and challenges

The studies mentioned in previous section provide great insights into the problem of locating alternative fuel stations. However, due to modeling challenges, a few critical issues remain as detailed hereafter. First, the uncertainty of refueling demand and its variation over time, if not carefully considered, can fundamentally fail the plan of refueling station deployment. Although there are a number of studies trying to predict the demand of AFVs [23,24,38], all with components accommodating randomness in the prediction, the refueling demand of AFVs in the existing studies on the location problem of refueling stations is considered as a known and fixed value. To the best knowledge of the authors, there is no study that has considered demand uncertainty for the refueling station location problem, while demand uncertainty has been incorporated in recent studies on general network design problems. Lou et al. [39] categorized these studies into two groups based on their modeling approaches. The first group employs the concept of reliability. Studies in this group either aim to maximize some reliability measure (e.g., [40]) or to satisfy a chance constraint when maximizing efficiency (e.g., [41]). The second group relies on the notion of robust design. The purpose is to design a network which can perform well under various circumstances, even in the presence of unpredicted high demand.

Second, the locations of refueling stations in a traffic network may also impact the route choice of travelers due to the probable need to deviate from their original routes for refueling. This can further result in change of traffic flow patterns and thereby link travel times of the network. Hence, a central planner may have to account for the impact of refueling stations on network traffic flows and the associated travel times, which has been ignored or simplified in most previous studies. For example, Miralinaghi et al. [22] proposed a new mathematical formulation of the refueling station location problem for hydrogen fuel vehicles, where the total costs are minimized through the planning horizon, including construction, operation and system travel costs of intra-city trips. They developed a game-theoretical framework in which travel time is constant, based on the assumption that refueling demand is negligible compared with total travel demand. Although Lee et al. [37] factored the effect of route choice of travelers on network travel times under the user equilibrium condition, they failed to propose the tractable model where refueling demand has to be met in traffic network. Furthermore, they ignored the effect of refueling delay of travelers which may cause to assign significant amount of refueling demands to one refueling station. Finally, they solved traffic assignment model using a Frank–Wolfe algorithm which has been shown as inefficient algorithm to derive accurate link flow patterns [42,43].

Research contributions of the study

To address the described research gaps between the current literature and the realism of AFV development, this study proposes two different mathematical models in the framework of facility location/network design problem for intra-city trips to incorporate the considerations of (i) refueling demand uncertainty of AFVs and (ii) route choice of travelers, respectively.

In the first model, named Robust Centralized Planning Model (RCPM), we formulate a refueling station location problem with demand uncertainty and thereby propose a robust optimization model. In this model, we consider multiple time periods as it is a key characteristic of refueling station location problems. While focusing on the effect of refueling demand uncertainty, link travel times of the network are assumed to be constant for simplicity in this model. Since the problem can not be solved due to complexity of the model using commercial solvers such as CPLEX, we develop a cutting-plane scheme to obtain the robust design of refueling station locations over the planning horizon.

The second model, Bi-Level Centralized Planning Model (BLCPM), relaxes the assumption that refueling stations do not have impact on link travel times of a traffic network. Link travel times are formulated as functions of link flows. The UE-based assignment framework is incorporated at the second level to capture the responses of travelers to the decisions made by the central planner regarding the locations of refueling stations at the first level. In addition to the consideration of both refueling and non-refueling travelers, the BLCPM features two more complexities compared with a typical bi-level NDP: (i) travelers incur delay in each refueling station, and (ii) under the user equilibrium condition, each refueling vehicle has to visit one refueling station. Reflecting these requirement in the model is not trivial. Even with a path-based model, multiple possibilities may exist as there may be more than one refueling station along the same path. Hence, a link-based modeling approach is formulated considering refueling delay which is more mathematically tractable compared to path-based formulation. It is solved using a genetic algorithm where the traffic assignment is solved using a complementarity assignment algorithm with higher solution accuracy compared to the Frank–Wolfe algorithm.

Two main aspects of AFV refueling stations within transportation infrastructure are considered in both models, namely, the number of refueling stations and their locations. Operating capacities are considered as external parameters in the first model. Although, we primarily focus on intra-city trips of hydrogen fuel vehicles whose driving range is near 300 miles, it is worth re-emphasizing that the driving range of other types of AFVs than hydrogen fuel vehicles is not a critical factor in intra-city trips. Therefore, the models and results of this research can be extended to determine refueling station location of other types of AFVs. For example, recent research [44] has found that the typical driving range of electrical vehicles is about 100 miles. It allows travelers to handle a large fraction of their daily trips in the urban areas with only one stop at one recharging location. Additionally, fast progression of battery technology has recently further enabled the auto industry to manufacture EVs with a 250-mile driving range in a single charge [45]. Hence, driving range is no longer a major issue towards the promotion of AFVs especially in the urban areas and thereby should not limit general applications of the proposed models.

Robust Centralized Planning Model (RCPM)

Refueling demand uncertainty is an inevitable element of hydrogen refueling station location problem. The prediction of demand for any new transportation technology is a major challenge for strategic planning. AFV is the most advanced technology in comparison to conventional vehicles. Because of unknown characteristics of future AFVs and unknown responses from travelers, it is very difficult to predict the market penetration rate of AFVs [23,24]. While demand uncertainty has been considered in many network design literatures, it has not been accounted for in any previous studies of refueling supply in a network modeling context.

In this section, we extend the formulation proposed by Miralinaghi et al. [22] for the refueling station location problem to further address demand uncertainty; hence, we also follow most of the assumptions adopted in Miralinaghi et al. [22]. First of all, for simplicity, we assume travel times are constant in this model. With constant travel times, non-refueling traffic will not affect the final traffic pattern, and therefore, can be negligible in this model. In the RCPM, travelers are classified based on O-D pairs. The refueling travelers of O-D pairs are denoted by set W in this section. Second, we also use the notion of multiple time periods in the model. The multi-period nature of the formulation represents the variations in the user preferences and traffic levels during planning horizon, as its importance is indicated by Chung and Kwon [46] and Miralinaghi et al. [22]. Third, travelers are assumed to deviate from the shortest path connecting their origins and destinations to refuel.

Mathematical formulation

Following the discrete robust optimization approach for traffic network design under uncertainty proposed by Lou et al. [39], an "uncertainty budget" K is introduced, and at most K O-D pairs are allowed to deviate from the nominal demand. In this approach, nominal demand represents the base case demand scenario. Let q_s^w, $s = 1, 2, \ldots, S_w$ denote the refueling demand for travelers of O-D pair w under scenario s and e_s^w is a binary variable indicates the realized scenario for travelers of O-D pair w. In this model, potential refueling locations are treated as a set of nodes $Z \subseteq N$, and c_z is the construction cost at node $z \in Z$. Note that construction costs are treated in annualized payment terms. With these considerations, decision variables for the planner include the locations for the refueling stations, y_z, and the percentage of travelers of O-D pair w to be assigned to refueling station z at time period t, denoted by $x_z^{w,t}$. The capacity of refueling station z, p_z, is considered to be a known parameter.

Note that refueling travelers will deviate from shortest path connecting their origins and destinations in order to refuel. We denote the shortest travel time for any traveler of O-D pair w passing a potential station z at time period t by $T_z^{w,t}$. Let β denote the value of time for travelers. The central planner's objective is then to minimize the sum of the total annualized construction costs with the cost of the total system travel time in the network. The robust formulation deals with the worst-case scenario. In this case, we consider the cost of the minimum system travel time under the worst-case demand scenario, i.e., a max–min formulation. The robust centralized planning model can be formulated as follows:

$$V = \min_{e,y}\left(\sum_{z\epsilon Z} c_z y_z + \max_{q}\min_{x}\beta\sum_{t\in\mathscr{T}}\sum_{w\in W} q^{w,t}\sum_{z\epsilon Z}\left(x_z^{w,t}\cdot T_z^{w,t}\right)\right) \quad (1)$$

$$\sum_{z\epsilon Z} x_z^{w,t} = 1,\ \ \forall t\in\mathscr{T},\ \ \forall w\in W \quad (2)$$

$$\sum_{w\in W} q^{w,t} x_z^{w,t} \le p_z\cdot y_z,\ \ \forall t\in\mathscr{T},\ \ \forall z\in Z \quad (3)$$

$$\sum_{s=1}^{S} e_s^{w,t}\cdot q_s^{w,t} = q^{w,t},\ \ \forall t\in\mathscr{T},\ \ \forall w\in W \quad (4)$$

$$\sum_{s=2}^{S}\sum_{(w,t)\in(W,\mathscr{T})} e_s^{w,t} \le K \quad (5)$$

$$\sum_{s\in S} e_s^{w,t} = 1,\ \ \forall t\in\mathscr{T},\ \ \forall w\in W \quad (6)$$

$$e_s^{w,t} \in \{0,1\}\quad \forall s\in S,\ \ \forall t\in\mathscr{T},\ \ \forall w\in W \quad (7)$$

$$y_z \in \{0,1\},\quad \forall z\in Z \quad (8)$$

$$x_z^{w,t} \ge 0,\ \ \forall t\in\mathscr{T},\ \ \forall z\in Z,\ \ \forall w\in W \quad (9)$$

Constraint (2) states that the refueling demand of each traveler of O-D pair in each time period has to be fulfilled by constructed refueling stations. Constraint (3) ensures that if some refueling demand is assigned to a station z, the station should be constructed. Also, this demand should not exceed the capacity, p_z, of station z. Constraint (4) ensures the refueling demand is met. Constraints (5)–(7) represent the uncertainty set of refueling demand. Constraint (5) specifies at most K O-D pair demands can deviate from the nominal plan which is referred as scenario 1 in the notation. Constraint (6) guarantees that only one demand scenario is realized for each O-D pair. Finally, Constraints (7)–(9) are integrality and non-negativity constraints for the decision variables, respectively.

To convert the model (1)–(9) to a min–max problem and apply well-established algorithms, the inner most minimization problem is dualized. Note that the only decision variable of the inner most problem is x_{ij}^w given the station locations y_z and the worst-case demand scenario. This dual replacement converts the main model to a min–max problem with objective function as follows:

$$V = \min_{e,y}\left(\sum_{z\epsilon Z} c_z y_z + \max_{\mu,\lambda,q}\sum_{(w,t)}\mu^{w,t} - \sum_{(z,t)}\lambda_z^t p_z y_z\right) \quad (10)$$

In this formulation, $\mu^{w,t}$ and λ_z^t are multipliers for constraints (2) and (3). Similar to Lou et al. [39], a cutting-plane scheme is adopted to solve the problem using four steps. The solution procedure can be described as follows:

Step 0. Initialization. Perform a greedy heuristic method and assign the refueling demand to the refueling stations with the lowest construction costs. Obtain the initial station locations $\bar{y}$. Set iteration counter k to 1.

Step 1. Solve the following mixed-integer nonlinear sub-problem to generate the worst-case scenario:

$$U = \max_{\mu,\lambda,q}\sum_{(w,t)}\mu^{w,t} - \sum_{(z,t)}\lambda_z^t p_z y_z \quad (11)$$

$$\mu^{w,t} - \lambda_z^t q^{w,t} \le \beta T_z^{w,t} q^{w,t},\quad \forall t\in\mathscr{T},\ \ \forall z\in Z,\ \ \forall w\in W \quad (12)$$

Then, set $k = k+1$.

Step 2. Incorporate the solution to the sub-problem in Step 1 in the constraint set of the model below. Find y and ξ that solve the robust centralized planning model:

$$V = \min_{y,\xi}\sum_{(w)} c_z y_z + \xi \quad (13)$$

$$\xi \ge \sum_{(w,t)}\mu_k^{w,t} - \sum_{(z,t)}\lambda_{z,k}^t p_z y_z,\ \ \forall t\in\mathscr{T},\ \forall z\in Z,\ \forall w\in W,\ \forall k = 1,\ldots,n \quad (14)$$

Step 3. If ξ is greater than U, Stop and report the current solution, $\{V, y\}$. Otherwise, go to Step 1.

Computational results

The algorithm for the robust centralized planning approach is coded in GAMS. The master problem, a mixed-integer model, is solved by the CPLEX solver [47]. The sub-problem is a mixed-integer nonlinear and SBB solver [48] is employed to solve the model. The robust centralized planning model is applied to the Sioux-Falls network, located in South Dakota, USA (Fig. 1). Detailed characteristics of the network including free flow travel times, link capacity, and origin-destination demands can be found in LeBlanc et al. [49]. Three possible demand scenarios, namely low, nominal, and high demand, are generated for each O-D pair. The constant path travel times are derived based on the user equilibrium conditions without considering travelers refueling needs. The value of travel time is set as one for cost conversion purposes. The construction costs of potential refueling station locations in nodes 6–18 is assumed to follow a uniform distribution with mean of $85,000 and standard deviation of $26,000. This assumption is based on reported annual investment cost of hydrogen refueling stations which varies between $40,000 and $175,000 depending on the size of refueling station [50].

To determine the efficiency of the robust plan obtained from the proposed model in comparison with the nominal plan where no demand uncertainty is considered, three sets of Monte Carlo simulations are performed with predetermined specific robust plan with three different levels of demand uncertainties. The level of uncertainty is represented here by the difference between the demand values under the low and the high scenarios in the proposed model. The larger the difference is, the higher the level of uncertainty is induced. The low and the high demand scenarios ($q_2^{w,t}$ and $q_3^{w,t}$, respectively) are generated based on the nominal demand as follows:

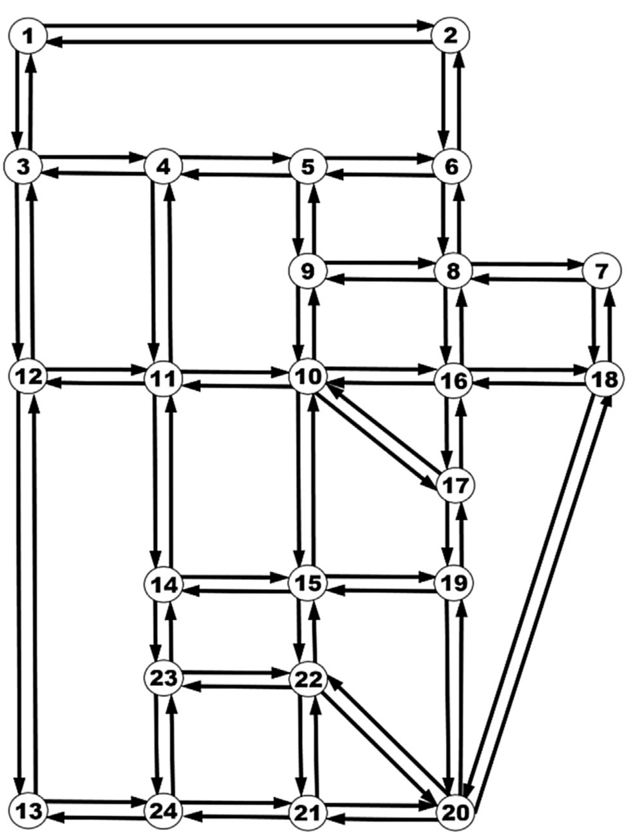


Fig. 1 – Sioux-Falls network.

$$q_2^{w,t} = (1-\alpha_L)\cdot q_1^{w,t}, \quad \forall w,t \tag{15}$$

$$q_3^{w,t} = (1+\alpha_R)\cdot q_1^{w,t}, \quad \forall w,t \tag{16}$$

where α_L and α_R are two parameters controlling the level of uncertainty. The three robust plans are obtained with α_L and α_R equal to (0.7, 0.7), (0.5, 0.5), and (0.3, 0.3) respectively.

It should be noted that it is possible that the obtained plans, both nominal and robust, might be infeasible under certain randomly generated demand scenarios when the total refueling demand is higher than the total station capacity. If such infeasibility occurs, the station location plans will be modified by opening additional stations at other candidate nodes. In other words, if the refueling demand generated causes infeasibility, a recourse problem is solved to update the plan. The total system travel time will then be calculated accordingly. The additional construction cost incurred will be counted as part of the overall cost of the station location plan under the particular demand vector.

Table 1 compares the performance of the nominal and the three robust plans. Four measures are identified as the performance measures to evaluate the reliability and efficiency of the plans. They are average construction cost, average system travel time, worst-case total system cost (including construction cost and system travel time), and the number of demand vectors generated that cause the original plan to be infeasible. In each simulation, 1000 realized demand vectors are generated with a continuous uniform distribution. The lower and upper bounds of the uniform distribution are set as the corresponding low and high demand values used to solve for the robust plans and they are represented in the first row of Table 1.

It is expected that construction cost for the nominal plan is less than that of the robust plans. Our results show that the average construction cost for nominal plan can become higher than robust plan when the uncertainty level is higher, due to the large number of infeasible demand vectors. For example, in the first simulation scenario, the average construction cost for nominal plan is higher than robust plan because of this reason. The resulting average total system travel time, worst-case total system cost, and the number of failures indicate that robust plans are more reliable as they lead to lower values (desirable) for all performance measures in all three simulation scenarios. The reductions in the worst-case total system cost for the three simulation scenarios are 8%, 2% and 3%, respectively. In addition, average total system travel time reduces by 6%, 7%, and 14% respectively if robust plan is adopted.

Thus far, we have examined the performances of the robust plans obtained from the proposed model when the uncertainty predictions are accurate. The simulation scenarios are generated based on the same parameters used in obtaining the robust plans. We are also interested in evaluating the performances of the robust plans obtained from not-so-accurate uncertainty predictions. For this purpose, nine additional simulation runs are performed. For these nine runs, demand vectors are generated from uniform distributions whose lower and upper bounds are not the

Table 1 – Performance of robust and nominal plans in simulations.

	Candidate nodes	Simulation scenario					
		$(0.3q_1^{w,t}, 1.7q_1^{w,t})$		$(0.5q_1^{w,t}, 1.5q_1^{w,t})$		$(0.7q_1^{w,t}, 1.3q_1^{w,t})$	
		Nominal	Robust	Nominal	Robust	Nominal	Robust
Plan	6	0	0	0	0	0	0
	7	1	1	1	1	1	1
	8	1	0	1	1	1	0
	9	1	1	1	1	1	1
	10	1	1	1	1	1	1
	11	0	1	0	1	0	0
	12	0	0	0	0	0	1
	13	0	1	0	0	0	0
	14	1	0	1	1	1	1
	15	1	1	1	0	1	1
	16	0	0	0	0	0	0
	17	0	0	0	1	0	0
	18	1	1	1	0	1	1
Performance measures	Average construction cost	435,730	401,000	346,000	379,000	346,000	376,000
	Average system travel time	104,133	97,946	108,085	100,260	108,071	93,029
	Worst-case total system cost	153,441	148,332	146,399	143,517	145,323	133,588
	Number of failures	216	106	0	0	0	0

same as the ones used in solving the robust plans. More specifically, α_R varies between 0.1 and 0.9, and α_L is fixed as 0.5.

Fig. 2 presents the average total system travel time of the nominal plan and the three robust plans obtained with $\alpha_L = \alpha_R = 0.3$, 0.5, 0.7 under nine simulation runs. It is clear that increasing the demand variation (α_L,α_R) leads to higher differences in average system travel time between the nominal plan and robust plans. The largest difference between the nominal plan and the robust plan obtained with $\alpha_L = \alpha_R = 0.7$. This is because this particular robust plan is more conservative and the associated total construction cost is also higher. It should be mentioned that all the three robust plans are able to handle every demand vector generated. Therefore, the average total construction cost remains the same for the robust plans under different simulation scenarios. However, the average construction cost for the nominal plan can increase from \$346,000 to \$488,500 when α_R is 0.9 because the robust plan is not able to accommodate every realized demand vector.

Bi-Level Centralized Planning Model (BLCPM)

In this section, we focus on the placement of hydrogen refueling stations to serve intra-city or short-distance trips by relaxing the assumption of constant travel time. With this consideration, the central planner should take the response of travelers into account in making the decision regarding the location to construct new refueling stations since the refueling location choice of travelers affect the travel time in the traffic network. To focus on this aspect of real-world problem, we have to make other simplifications: (i) we assume that travel demand is deterministic; and (ii) we only consider a single-period. These assumptions are made for

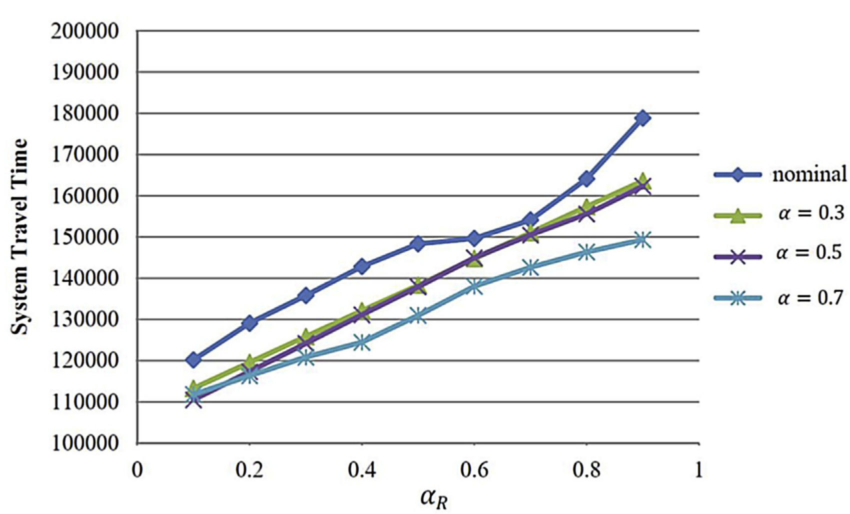


Fig. 2 – Comparison of nominal plan and robust plans for Sioux-Falls network.

simplicity and hence, we focus on the effect of route choice of travelers on the location of hydrogen refueling stations. The proposed BLCPM can be modeled as a bi-level program. The transportation planner is the leader in this problem, and the corresponding upper-level problem aims to minimize the sum of the construction cost, total system travel time/cost, and the cost of delays experienced by the refueling travelers at refueling stations in the network. In the lower-level problem, travelers are the followers who will adjust their refueling stops and route choices to reduce their generalized cost according to the user equilibrium condition based on the refueling station locations. Unlike previous studies in this area, the proposed model considers both refueling and non-refueling travelers while we develop the link-based formulation of the problem. Since travel times are treated as a function of link flows, the non-refueling flows cannot be ignored as they will also contribute to the link travel times, and thus, the final equilibrium traffic pattern. Therefore, the problem is essentially a multi-class user equilibrium.

Another, perhaps the most unique, feature of the proposed BLCPM is the modeling approach for flow conservation for refueling traffic. First of all, the total flow passing through refueling stations in the network should be equal to the total refueling demand. In contrast to RCPM, in BLCPM, the travelers are defined by both refueling needs and O-D pairs. Furthermore, it is assumed that a refueling vehicle will only make one stop during its trip because the driving range of hydrogen fuel vehicles is also not a concern in the intra-city trips. Our assumption would reduce the number of augmented paths for refueling travelers significantly, but would still require a path-based model with a considerably large amount of augmented paths. To the best of our knowledge, there is no equivalent link-based formulation under any of the two aforementioned considerations. This is because a link-based formulation relies on the idea of shortest path trees where every subset of the tree starting from the root node up to a certain intermediate node is also the shortest path to that particular node [51,52]. However, a fastest refueling route (including both travel time and refueling delay) does not require every subpath to be the shortest. Considering the top path in the small network shown in Fig. 3, we suppose there are two refueling stations along this path, one on link (1, 2) and the other on link (3, 4). The two stations have the same delay time. A traveler could refuel at the first station, or wait until the second station to refuel. In the former case, the augmented subpath that consists of link (1, 2) and the refueling station is not the shortest augmented path from node 1 to node 2. In order to eliminate the need for enumerating every possible augmented paths and to enhance the mathematical tractability of the model, this study further assumes that all refueling travelers taking the same path make their stops at the same station.

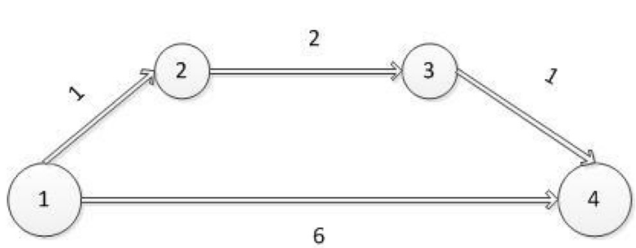


Fig. 3 – Network with two paths.

This assumption is necessary to establish a link-based formulation of the problem. Together with the aforementioned condition that the flow passing through refueling stations should equal to the total refueling demand, this assumption ensures the flow conservation condition is modeled correctly. Without this assumption, the model could lead to invalid flow patterns. We further demonstrate this concept using the small network in Fig. 3. Suppose there is only one origin-destination (O-D) pair (1, 4) with a refueling demand of two and zero non-refueling demand. Link travel times are presented beside each link in Fig. 3. Suppose the delay functions of the two refueling stations, one on link (1, 2) and the other on link (3, 4), are the same and follow a simple linear function $d(x) = x$. Consider the following flow pattern on the network where one unit of travelers take path 1-2-3-4, and the remaining travelers take path 1–4. It is obvious that this flow pattern is invalid as there is no station along link (1, 4) to fulfill the refueling demand of the one unit of travelers taking that path. However, without the assumption that travelers will only stop once to refuel and that travelers along the same path will stop at the same station, the model would allow the one unit of travelers following the top path to stop at both stations. The resulting flow pattern would satisfy the user equilibrium condition as well as the flow conservation condition. First, the generalized cost (travel time plus refueling delay) of both paths are the same. Moreover, the total flow passing through refueling stations is equal to the refueling demand. This example demonstrates that it is necessary to employ the assumption that all refueling travelers taking the same path will make their stops at the same station. Note that this assumption does not restrict the travelers from the same O-D pair refuel at the same station. The demand from a particular O-D pair can still be assigned to different paths and refueled at different stations.

Mathematical formulation

With the above considerations, the problem can be mathematically modeled as follows. Consider a general network $G = (N, A)$ with node set N and link set A. Let W denote the set of travelers defined by O-D pairs and refueling needs. Refueling travelers and non-refueling travelers for the same O-D pair are treated as two separate groups. Let W_1 and W_2 denote the refueling and non-refueling travelers, respectively. Let v_{ij}^{w} denote the flow of link (i, j) serving refueling demand of travelers of O-D pair $w \in W_1 \cup W_2$. Let q^w denote the demand for traveler of O-D pair w. Further, let h_i^w represent the net total supply for travelers of O-D pair $w \in W_1 \cup W_2$ at node $i \in N$. By definition, $h_i^w = q^w$ if i is the origin, $h_i^w = -q^w$ if i is the destination, and $h_i^w = 0$ if i is neither origin nor destination of travelers of O-D pair w. Potential refueling stations are denoted by Z, and are modeled as a set of existing links in the BLCPM. The travel time and flow on link $(i, j) \in A$ is denoted by $t_{ij}(v_{ij})$ and v_{ij}. The refueling delay at the station on link (i, j) is $d_{ij}(v_{ij})$. The binary variable indicating whether a station location along a line (i, j) is denoted by y_{ij}. Further, define x_{ij}^{w} as follows:

$$x_{ij}^{w} = \begin{cases} 1 & \text{If travelers of } O-D \text{ pair } w \text{ passes refueling station of link}(i,j) \\ 0 & \text{otherwise} \end{cases}$$

With these notions, the bi-level program can be formulated in the form of a mathematical program with complementarity constraints (MPCC) as follows:

$$\min_{\nu,\mathbf{x},\mathbf{y}} \sum_{(i,j)} \beta \cdot \nu_{ij} \cdot t_{ij}(\nu_{ij}) + \sum_{(i,j)} \left(c_{ij} + \beta \cdot \nu_{ij}^{w_2} d_{ij}\left(\nu_{ij}^{w_2}\right)\right) \cdot y_{ij} \tag{17}$$

$$\sum_{j\in A\cup Z} \nu_{ij}^{w} - \sum_{j\in A\cup Z} \nu_{ji}^{w} = h_i^{w}, \quad w\in W_1\cup W_2 \tag{18}$$

$$\sum_{(i,j)\in Z} x_{ij}^{w} \cdot \nu_{ij}^{w} = q^{w}, \quad w\in W_1 \tag{19}$$

$$\nu_{ij} = \sum_{w} \nu_{ij}^{w}, \quad (i,j)\in A\cup Z \tag{20}$$

$$x_{ij}^{w} \le y_{ij}, \quad w\in W_1,\ (i,j)\in Z \tag{21}$$

$$\nu_{ij}^{w}\left(t_{ij}(\nu_{ij}) + \pi_i^{w} - \pi_j^{w}\right) = 0, \quad w\in W_2,\ (i,j)\in A\cup Z \tag{22}$$

$$t_{ij}(\nu_{ij}) + \pi_i^{w} - \pi_j^{w} \ge 0, \quad w\in W_2,\ (i,j)\in A\cup Z \tag{23}$$

$$\nu_{ij}^{w}\left(x_{ij}^{w}\cdot\left(d_{ij}\left(\nu_{ij}^{w}\right) + M\right) + t_{ij}(\nu_{ij}) + \pi_i^{w} - \pi_j^{w}\right) = 0, \quad w\in W_1,\ (i,j)\in Z \tag{24}$$

$$x_{ij}^{w}\cdot\left(d_{ij}\left(\nu_{ij}^{w}\right) + M\right) + t_{ij}(\nu_{ij}) + \pi_i^{w} - \pi_j^{w} \ge 0, \quad w\in W_1,\ (i,j)\in Z \tag{25}$$

$$x_{ij}^{w}, y_{ij}\in\{0,1\}, \quad w\in W_1,\ (i,j)\in Z \tag{26}$$

$$\nu_{ij}^{w} \ge 0, \quad w\in W_1\cup W_2,\ (i,j)\in A\cup Z \tag{27}$$

In the proposed mixed-integer nonlinear program (MINLP), π_i^{w} is an intermediate variable representing the node potential of node i for travelers of O-D pair $w\in W_1\cup W_2$. The objective function represents the total cost including the cost of total system travel time, the delay at refueling stations, and the construction cost of selected stations. Equations (18)–(20) represent a set of flow conservation equations. These constraints state that all refueling and non-refueling O-D trips have to be assigned to the network, and that the total flow passing through refueling stations is equal to the total refueling demand. Constraint (21) ensures that a refueling station will only be utilized when it is constructed. Constraints (22)–(25) are the link-based user equilibrium condition for non-refueling and refueling travelers. Link (i, j) is utilized only when it is part of the shortest path tree for travelers of O-D pair w. To ensure the assumptions discussed earlier, a big constant, denoted by M, is introduced as a penalty to make sure travelers will not stop at two or more refueling stations. Equation (27) is non-negativity constraint for link flows.

According to the conceptual scheme of our model, y_{ij} is the binary variable controlled by the planner, whose goal is to minimize the sum of the construction cost, the total system travel time, and the total refueling delay, where the travelers are only concerned about their own travel time and refueling cost. Referring to the general bi-level formulation, in our model the objective function and Equations (21) and (26) are the planner's problem to determine the best locations in the network, while constraints (22)–(25) are the user equilibrium conditions that replace the lower level traffic assignment problem. The proposed model (17)–(27) is a MPCC, a special type of mathematical program with equilibrium constraints. It is very difficult to solve MPCC because they are non-convex and non-smooth, and the constraint qualifications, typically assumed to prove convergence of standard nonlinear program (NLP) algorithms, often fail for MPCC (17)–(27). Hence, we discuss about the problem convexity in next subsection and then, we develop an algorithm to efficiently solve the model for large scale models.

Problem complexity

Finding optimal locations for refueling stations, using a bi-level mixed-integer nonlinear program, has two main computational complexities. The first complexity, the more challenging one, arises from the combinatorial nature of the problem. For a problem instance with N candidate refueling stations, there are 2^N-1 alternative solutions to be evaluated (-1 stands for the solution with no refueling stations, which is infeasible). Therefore, the feasible solution space of the problem explodes exponentially as the number N increases. The second complexity of the problem is associated to solving the traffic assignment sub-model for each alternative solution. As a time-consuming procedure, the traffic assignment is a necessary component of the bi-level problem to incorporate users' route choice behavior in response to various design alternatives.

The combinatorial explosion of the problem in the upper-level and the traffic assignment in the lower level render the exact solution of the problem intractable. The studies of similar bi-level problems (e.g. the discrete network design problem) indicate that, as the problem enlarges, it requires a significant run-time (e.g. few years) to obtain the *global* optimal solution of the problem [53], and even application of novel computational techniques such as parallel processing cannot help much in such cases [54].

Because of these issues, the commercial optimization packages of GAMS (such as simple branch and bound solver) are not able to solve the model even for a small network. To overcome the computational complexities, we develop a well-designed solution algorithm based on Genetic Algorithm with two elements: (1) trade-off between the run-time and the quality of the solutions, and (2) apply an efficient traffic assignment tool to tackle the sub-model. We discuss these points in more details in the next two sub-sections, respectively.

Genetic algorithm

Genetic algorithm is categorized as a population-based metaheuristic algorithm which has been extensively used in solving hard combinatorial problems [55]. The algorithm is inspired from the "survival of the fittest" principle in the theory of evolution. In a general description, a genetic algorithm starts with a set of random initial solutions, namely the initial population. In each iteration, it moves from one generation to another generation by selecting two high-quality parents (solutions) from the current population, performing *cross-over* and *mutation* functions over the parents, and introducing the resulting solution to the new generation. A detailed description of genetic algorithms can be found, for example, in the study of Gen and Cheng [55].

In the case of the problem in this paper, a solution can be simply encoded as a binary N-length string, $Y = [y^{(n)}]_{n=1-N}$, in

Input: The transportation network, refueling and non-refueling demand matrices, candidate refueling stations, etc.
Output: Locations of the refueling stations

// **Initialization**
Define the sets $\boldsymbol{\Pi}$ and $\boldsymbol{\Pi^B}$ and set them to {}.
For $p = 1$ to #$\boldsymbol{P}$
  Generate a new random solution, *new_sol*.
  Perform a traffic assignment and evaluate the total cost for *new_sol*.
  Add *new_sol* to $\boldsymbol{\Pi}$.
End For
For $p = 1$ to #$\boldsymbol{BP}$
  Remove the solution with minimum total cost, *min_sol*, from $\boldsymbol{\Pi}$.
  Add *min_sol* to $\boldsymbol{\Pi^B}$.
End For
Define ***best_sol*** and set it to the solution with minimum total cost in $\boldsymbol{\Pi^B}$.

// **The main loop of the genetic algorithm**
For $g = 1$ to #$\boldsymbol{G}$
  Set $\boldsymbol{\Pi}$ to {}.
  // **Generating new solutions**
  For $p = 1$ to #$\boldsymbol{P}$
    Randomly select two different solutions, *Parent*#1 and *Parent*#2, from $\boldsymbol{\Pi^B}$.
    // **Cross-over**
    Define a new solution *new_sol*.
    Copy one half of the decisions in *new_sol* from *Parent*#1 and the other half from *Parent*#2.
    // **Mutation**
    For n = 1 to N
      With probability ρ, change the binary decision $y^{(n)}$ in the *new_sol* to $\neg y^{(n)}$.
    End For
    // **The fitness function evaluation**
    Perform a traffic assignment and evaluate the total cost for *new_sol*.
    Add *new_sol* to $\boldsymbol{\Pi}$.
  End For
  // **Selecting the best solutions**
  Define the set of all existing solutions, Π^{all}, as $\boldsymbol{\Pi^B} \cup \boldsymbol{\Pi}$.
  Set $\boldsymbol{\Pi^B}$ to {}.
  For $p = 1$ to #$\boldsymbol{BP}$
    Remove the solution with minimum total cost, *min_sol*, from Π^{all}.
    Add *min_sol* to $\boldsymbol{\Pi^B}$.
  End For
  // **Updating the best solution found so far**
  Update ***best_sol*** to the solution with minimum total cost in $\boldsymbol{\Pi^B}$.
End For

Fig. 4 – The genetic algorithm for the bi-level problem.

which N is the total number of candidate refueling stations. In such a string, if $y^{(n)}$ is 1, it implies that the nth refueling station is decided to be constructed. Otherwise, if $y^{(n)}$ is 0, the nth refueling station is not constructed. The following parameters/notations also need to be introduced prior to detailed description of the proposed genetic algorithm:

Π: set of all solutions in the new population,
Π^B: set of the best solutions,
$\#P$: population size (i.e., the number of solutions in Π),
$\#BP$: best population size (i.e., the number of solutions in Π^B),
best_sol: best solution found by the genetic algorithm,
$\#G$: number of maximum generations in the genetic algorithm,
ρ: a probability used for *mutation* in the genetic algorithm.

Using the above notations, Fig. 4 presents the steps of the genetic algorithm developed in this study. As Fig. 4 shows, the algorithm starts by initialization, in which the two sets Π and Π^B are defined and initially set to empty (line 1). Then, $\#P$ random solutions are generated, evaluated using the traffic assignment tool, and added to the current population of solutions (lines 2–6). Afterward, the set of best solutions (i.e., the solutions with minimum total cost values) is made (lines 7–10) and the best solution is defined and set (line 11).

Table 2 – The calibrated parameters in the genetic algorithm.

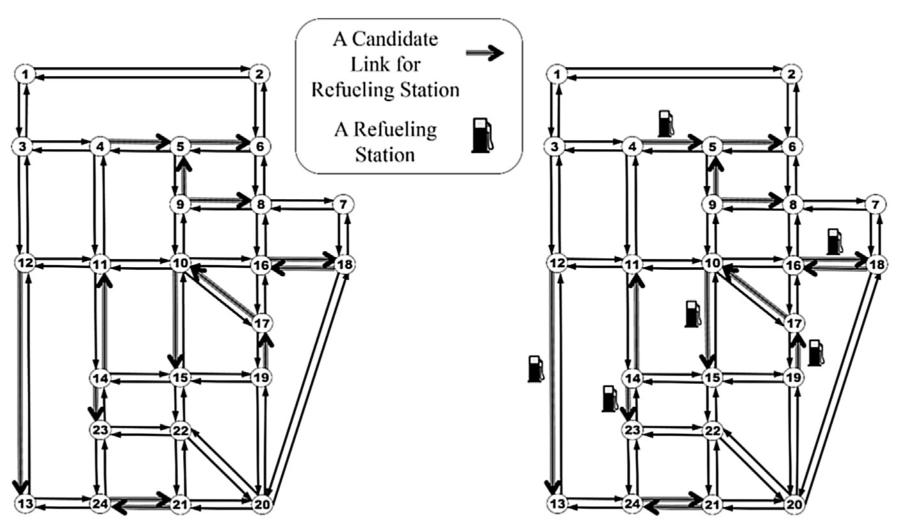
Parameters	Values
$\#P$	$2 \times N$
$\#BP$	$0.8 \times N$
ρ	0.15

Through the iterations of the algorithm (lines 12–31), first, the population corresponding to the new generation (iteration) is set to empty (line 13). Then, two random solutions *Parent#1* and *Parent#2* are selected from the current best population (line 15) in order to generate $\#P$ new solutions (lines 14–23), iteratively. In the cross-over step, a new solution is generated by copying one half of the decision variables from *Parent#1* and the other half from *Parent#2* (lines 16–17). The decision variables are finalized in the mutation step, in which each binary decision $y^{(n)}$ is changed with the probability ρ (lines 18–20). Finally, the new solution is evaluated by the assignment tool (line 21), and inserted into the new population (line 22). After $\#P$ new solutions are generated and evaluated (lines 14–23), the new set of best solutions is made by picking up the $\#BP$ existing solutions with the minimum total costs (lines 24–29) and the best solution is updated (line 30). The entire process of the genetic algorithm (the main loop i.e., lines 12–31) terminates after the algorithms reaches the total number of $\#G$ generations.

Table 2 briefly shows the values of calibrated parameters used in the genetic algorithm developed in this study. As mentioned earlier for $Y = [y^{(n)}]_{n=1-N}$, N in this table is the total number of candidate refueling stations. It must be also noted that the only parameter not calibrated here is $\#G$, which will change due to the problem size.

Traffic assignment

As a sub-problem of the bi-level problem in this paper, the traffic assignment aims at evaluating each solution through modeling users' route choice behavior in response to the locations of refueling stations. The accuracy of the traffic assignment is an essential factor in evaluation of different solutions. In the literature of traffic assignment algorithms, the Relative Gap (RG) is an extensively used measure to investigate the accuracy of algorithms (e.g. see Ref. [42]). It



(a) 14 Candidate Links for Refueling Stations
(b) Optimal Locations of Refueling Stations Obtained by Exhaustive Enumeration

Fig. 5 – The Sioux-Falls bi-level problem with 14 candidate links.

measures the gap between users' Total Travel Times (*TTT*) in the current assignment solution and the ideal Shortest Path Travel Times (*SPTT*) [40]. Generally, the relative gap may be defined as follows:

$$RG = ((TTT - SPTT))/TTT \tag{28}$$

In MPCC (17)–(27), based on two classes of refueling and non-refueling users, *SPTT* can be written as $SPTT = \sum_{w \in W_1} q^{W_1} T^{W_1} + \sum_{w \in W_2} q^{W_2} T^{W_2}$, where T^{W_1} and T^{W_2} are the shortest path travel times of refueling and non-refueling O-D pairs, respectively. As the assignment algorithm gets closer to the *equilibrium* situation (i.e., ideal shortest paths), the numerator in (28) and the RG get closer to zero.

Various traffic assignment algorithms have been introduced in the literature. The Frank–Wolfe algorithm is one of these algorithms which has been widely applied in many urban decision making problems, mainly due to its simplicity and less memory requirements. However, a debated flaw about this algorithm is that it reveals a sub-linear convergence behavior and cannot obtain sufficiently precise solutions in terms of *RG* measure. As the literature of traffic assignment shows, the Frank–Wolfe algorithm fails to achieve solutions with $RG \leq 10^{-4}$, which is required to fulfill basic urban planning functions [42,43]. Nevertheless, it has been used in location problems for refueling stations (e.g., see Lee et al. [37]).

To achieve high-accuracy solutions at the stage of solving traffic assignment problems, we use a complementarity assignment algorithm which has been introduced by Aashtiani [56]. The complementarity assignment algorithm, not only can achieve *RG* values close enough to zero, but also lends itself well to efficient numerical schemes in decision making problems [57–59]. A detailed discussion description about the functionality of this assignment algorithm is beyond the scope of this study and can be found in Refs. [56,60].

Computational results

In this sub-section, numerical experiments are conducted using the Sioux-Falls network to (i), test the quality of the solutions obtained by the genetic algorithm, (ii) determine the performance and run-times of the proposed algorithm, and (iii) show the effect of refueling demand share on the solutions of the algorithm. Here, it is assumed that:

- Link travel times follow the traditional Bureau of Public Roads (BPR) delay function.
- For those travelers refueling at link (i, *j*), there is an extra delay function, as in Equation (29), in which v_{ij} is the amount of refueling traffic flow, $a = 4$ min, and $b = 10^{-8}$ min/(veh/hour)^2.

$$d_{ij}(v_{ij}) = a + b v_{ij}^2 \tag{29}$$

- The average construction cost of each refueling station is $85,000.
- An average 10% of the total traveling demand at each O-D pair belongs to refueling users, in Sub-sections Quality of the solutions and Performance of the algorithm.

The entire solution algorithm (i.e., the genetic algorithm and the assignment tool) are implemented in Java programming language and run on a laptop with Windows 8, Intel(R) Core(TM) i5–4200U CPU@1.60 GHz and 8.00 GB memory.

Quality of the solutions

In this subsection, we test the quality of the solutions obtained by the genetic algorithm with considering 14 refueling links as depicted in Fig. 5(a). An exhaustive enumeration over $2^{14}-1 = 16{,}383$ solutions is conducted to search for the global optimal solution of the problem. The entire search is performed in 381.9 s. Fig. 5(b) shows the optimal solution of the problem, consisting of 6 refueling stations. In this solution, the total travel time of non-refueling and refueling users are 8,161,195 and 167,817 min, respectively. Therefore, the optimal objective value (i.e. minimum total costs) of the problem, is $8,161,195 + $167,817 + (6 × $85,000) = $8,839,012.

Due to the inherent randomness in the genetic algorithm (i.e., random initial population, cross-over, and mutation), the program is executed for 30 independent runs with #G = 15 number of genetic generations. Interestingly, the algorithm was observed to obtain the optimal solution of the problem, i.e. the solution in Fig. 5(b), in 27 runs. In the other 3 runs, the total costs of the obtained solutions were only 0.07%, 0.12%, and 0.26% more than the global optimal value. The average run-time of the genetic algorithm was 13.2 s with standard deviation of 0.6 s.

Performance of the algorithm

A large instance of the problem in the Sioux-Falls network is considered with 25 candidate links, as in Fig. 6(a), to explore the performance of the solution algorithm. Due to the large solution space of the problem, the number of generations, #G, is increased to 40 to allow for a more extensive search by the genetic algorithm. After 30 independent runs of the program, the average objective function values and run-times were 8,709,526 min and 62.6 s, with standard deviations of 4559 min and 12.2 s, respectively. Fig. 6(b) shows one of the solutions obtained by the genetic algorithm with 5 refueling stations and total travel times of 8,120,338 and 169,348 min for non-refueling and refueling users, respectively. For the solution depicted in Fig. 6(b), the values of run-time, and objective function during #G = 40 iterations of the algorithm are shown in Fig. 7. The total costs of the best found solution (i.e., objective value) sharply reduces within the first iterations of the algorithm, but has a rather low reduction afterward, as observed in Fig. 7. Regardless of the amount of improvement in the objective value, the required run-time remains linear with respect to the number of iterations in the genetic algorithm.

Analysis on the refueling demand share

To understand the effect of the refueling demand share, we consider the Sioux-Falls example in Fig. 6(a) with 25 candidate refueling stations. So far, it was assumed that the refueling demand share is 10% at each O-D pair. In this sub-section, the average values of minimum total travel times for refueling and non-refueling users as well as the number of refueling stations can be observed in Fig. 8(a)–(c), respectively.

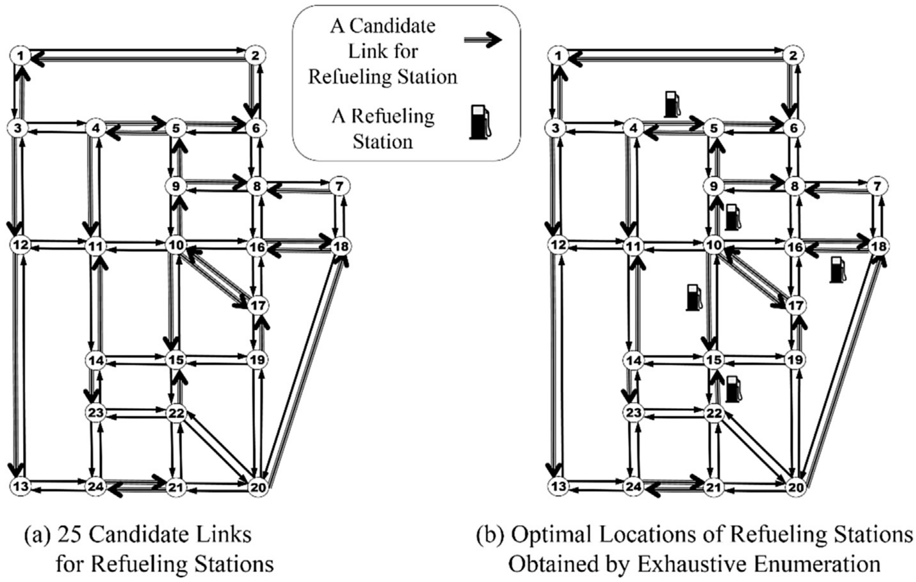


Fig. 6 — The Sioux-Falls bi-level problem with 25 candidate links.

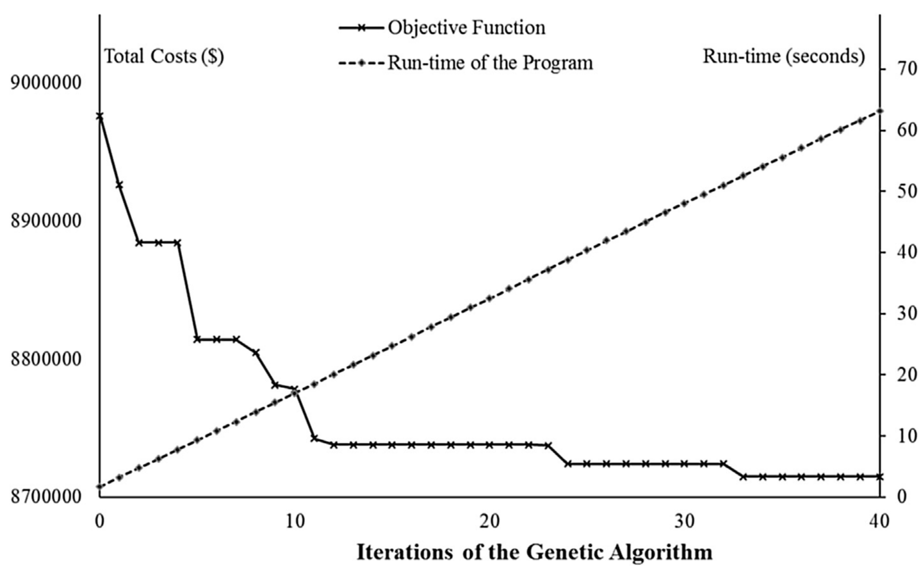


Fig. 7 — The values of run-time and objective function through iterations of the genetic algorithm.

Fig. 8 illustrates that as the refueling demand share increases, more refueling stations are added to the network to serve the refueling demand. Further, the total travel time of refueling users increases with respect to their refueling demand share since the deviation of travelers from their shortest paths results in higher total system travel time. For non-refueling users, the total travel time has a general increasing trend as well. This observation can be justified due to the fact that non-refueling and refueling users share the same roads in the network and the effect of congestion is transmitted from refueling users to non-refueling ones. However, the slope of increasing trend of the total travel times for non-refueling users reduces as their trip demand is reduced, or in other words, as the refueling demand share in Fig. 8(b) increases. This positive slope reduces because, as the refueling demand share increases, the marginal cost of travelers' deviation from their shortest paths decreases and hence, the increasing trend of total system-travel time reduces.

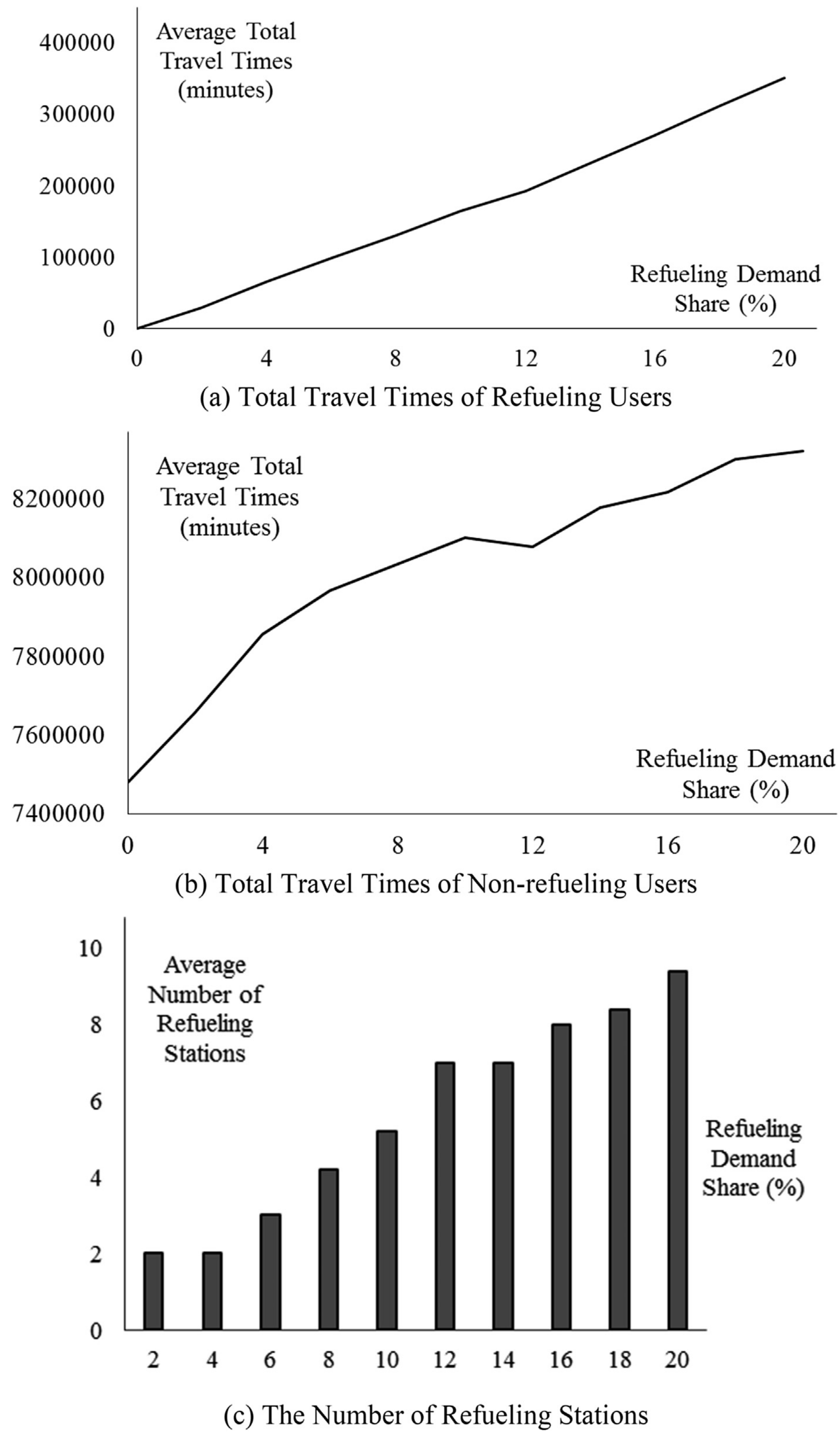


Fig. 8 – The effect of refueling demand share over the solution of the problem.

Conclusions

This paper proposed two mathematical formulations for the refueling station location problem in a traffic network for hydrogen fuel vehicles. The goal is to minimize the sum of the total construction cost, the total system travel time, and the refueling delay, while factoring the realism of AFV market development and network traffic dynamics. Since the driving range of hydrogen fuel vehicles is not a concern in intra-city trips, it is assumed that drivers will refuel only once during their trips. The first formulation in RCPM considers demand uncertainties in light of the difficulty to predict the future market penetration rates of AFVs. To the authors' best knowledge, this is the first study to incorporate demand uncertainty in the refueling station location problem. A discrete robust optimization approach is employed to formulate this problem as a min-max-min program. To solve the model, the formulation is first converted to a min–max problem. A cutting plane algorithm is utilized to solve the robust centralized planning model. Numerical results demonstrate the benefits of considering demand uncertainty in the model. It can lead to more reliable designs that will render smaller average as well as worst-case total system travel time. Though the initial construction cost of a robust plan might be higher, it may save more money in the future since it is able to handle a wider range of realized demand vectors. By contrast, the nominal plan may fail with a higher frequency to accommodate the total realized refueling demand in the network.

In the second model, it is assumed that travelers are able to select which station to refuel together with the shortest refueling path. Link travel times are treated as nonlinear functions of link flows in the BLCPM. Drivers traveling along the same path are assumed to stop at the same refueling station. This problem is formulated as a bi-level NDP, where the first level determines refueling station locations and the second level captures demand-side responses using the modeling framework of UE assignment. A link-based bi-level formulation is proposed for the problem that is more mathematically tractable compared to path-based models, while link travel times are formulated as the functions of link flows. The genetic algorithm is developed to solve the bi-level NDP, where the lower level problem is solved using a complementarity assignment algorithm. The proposed solution algorithm has been shown to efficiently reach high quality solutions for the problem. It is also demonstrated that as the refueling share of the travel demand increases, the total system travel times increases while the effect of travelers' deviation on total system travel time is less under high refueling demands compared to low ones.

In summary, the two proposed models contribute to the literature by respectively addressing two critical demand-side modeling challenges in the problem context of deploying refueling stations to develop the market of hydrogen fuel vehicles. RCPM focuses on the robust design to determine the locations of refueling stations in a traffic network, subject to the uncertainty of refueling demand; the uncertainty can be further factored to various unknown causes along the course of AFV market development for extended applications. On the other hand, BLCPM more explicitly models network traffic dynamics by adopting nonlinear link travel time functions, refueling delays and AFV driver's route choice behavior upon refueling needs is accounted for in the UE condition of the traffic network with behaviorally justifiable assumptions.

This study is the first step towards a more practical approach to the refueling station location problem for renewable energy. A range of practical considerations, such as demand uncertainty, nonlinear travel time function and multiple time periods, are incorporated in the model formulation, which enables decision-makers to more efficiently and robustly deploy refueling stations for hydrogen fuel vehicles in urban areas, in response to the likely development course of market demand. To this end, the study can be helpful in long-term transportation planning to promote extensive use of AFVs and renewable energy. A future research direction is to develop an efficient algorithm to solve the BLCPM for large traffic network over the multiple time periods. Another future research direction is to relax the assumption of BLCPM model in which refueling travelers of the same path are assumed to stop at the same refueling station. A third future research direction is to develop both RCPM and BLCPM for inter-city trips with consideration of driving range.

Acknowledgements

We wish to thank Dr. Yu-Ting Hsu of the National Taiwan University and Ms. Sania Esmaeilzadeh Seilabi for sharing their valuable comments on an earlier draft of the paper.

REFERENCES

[1] Tavakkoli S, Lokare OR, Vidic RD, Khanna V. Systems-level analysis of waste heat recovery opportunities from natural gas compressor stations in the United States. ACS Sustain Chem Eng 2016;4:3618–26. http://dx.doi.org/10.1021/acssuschemeng.5b01685.

[2] Ghorashi AH, Rahimi A. Renewable and non-renewable energy status in Iran: art of know-how and technology-gaps. Renew Sustain Energy Rev 2011;15:729–36. http://dx.doi.org/10.1016/j.rser.2010.09.037.

[3] Fourth Carbon Budget Review – technical report. n.d. https://www.theccc.org.uk/wp-content/uploads/2013/12/1785b-CCC_TechRep_Singles_Book_1.pdf. [Accessed 17 February 2016].

[4] Miralinaghi M, Peeta S. Multi-period equilibrium modeling planning framework for tradable credit schemes. Transp Res Part E Logist Transp Rev 2016;93:177–98. http://dx.doi.org/10.1016/j.tre.2016.05.013.

[5] Miralinaghi M, Peeta S, He X, Ukkusuri SV. Managing morning commute congestion with a tradable credit scheme under commuter heterogeneity and market loss aversion behavior. Transp. Res. Board 96th annu. Meet. (No. 17–01040). 2017.

[6] Khalilikhah M, Habibian M, Heaslip K. Acceptability of increasing petrol price as a TDM pricing policy: a case study in Tehran. Transp Policy 2016;45:136–44. http://dx.doi.org/10.1016/j.tranpol.2015.09.014.

[7] Talebpour A, Mahmassani HS, Hamdar SH. Modeling lane-changing behavior in a connected environment: a game

theory approach. Transp Res Part C Emerg Technol 2015;59:216–32. http://dx.doi.org/10.1016/j.trc.2015.07.007.
[8] Miralinaghi S. Refueling station location problem for renewable energy in a transportation network with multiple time periods, nonlinear delay, and autonomous users. The University of Alabama; 2012.
[9] Mak H-Y, Rong Y, Shen Z-JM. Infrastructure planning for electric vehicles with battery swapping. Manag Sci 2013;59:1557–75. http://dx.doi.org/10.1287/mnsc.1120.1672.
[10] Adler JD, Mirchandani PB, Xue G, Xia M. The electric vehicle shortest-walk problem with battery exchanges. Netw Spat Econ 2014. http://dx.doi.org/10.1007/s11067-013-9221-7.
[11] U.S. Energy Information Administration. Annual energy review 2010. Washington, DC. 2011.
[12] International Energy Agency. World energy outlook: China and India insights. Paris, France. 2007.
[13] Melendez M. Transitioning to a hydrogen future: learning from the alternative fuels experience. Golden, CO. 2006.
[14] Soltani-Sobh A, Heaslip K, Bosworth R, Barnes R. Compressed natural gas vehicles. Transp Res Rec J Transp Res Board 2016;2572:28–36. http://dx.doi.org/10.3141/2572-04.
[15] Soltani-Sobh A, Heaslip K, Bosworth R, Song Z. An aggregate time series analysis to investigate effect of Compressed Natural Gas (CNG) Vehicles on Vehicle Miles Traveled (VMT). Int J Mech Eng Autom 2016;3:399–413.
[16] Lin Z, Ogden J, Fan Y, Chen CW. The fuel-travel-back approach to hydrogen station siting. Int J Hydrogen Energy 2008;33:3096–101. http://dx.doi.org/10.1016/j.ijhydene.2008.01.040.
[17] Alternative Fuels Data Center. Alternative fueling station locator. 2015. http://www.afdc.energy.gov/locator/stations/ [Accessed 22 June 2015].
[18] California Fuel Cell Partnership. A California road map: the commercialization of hydrogen fuel cell vehicles. West Sacramento, CA. 2014.
[19] FCCJ. Commercialization scenario for FCVs and H_2 stations. 2010. http://www.fccj.jp/eng/index.html.
[20] Kang JE, Recker W. Strategic hydrogen refueling station locations with scheduling and routing considerations of individual vehicles. Transp Sci 2014:1–17.
[21] Stephens-Romero SD, Brown TM, Carreras-Sospedra M, Kang JE, Brouwer J, Dabdub D, et al. Projecting full build-out environmental impacts and roll-out strategies associated with viable hydrogen fueling infrastructure strategies. Int J Hydrogen Energy 2011;36:14309–23. http://dx.doi.org/10.1016/j.ijhydene.2011.08.005.
[22] Miralinaghi M, Keskin BB, Lou Y, Roshandeh AM. Capacitated refueling station location problem with traffic deviations over multiple time periods. Netw Spat Econ 2016. http://dx.doi.org/10.1007/s11067-016-9320-3.
[23] Ye JJ. Optimality conditions for optimization problems with complementarity constraints. SIAM J Optim 1999;9:374–87. http://dx.doi.org/10.1137/S1052623497321882.
[24] Cao X, Mokhtarian PL. The future demand of alternative fuel passenger vehicles: a diffusion of innovation approach. Davis, CA: University of California; 2004.
[25] Miralinaghi M, Lou Y, Hsu Y-T, Shabanpour R, Shafahi Y. Multiclass fuzzy user equilibrium with endogenous membership functions and risk-taking behaviors. J Adv Transp 2016. http://dx.doi.org/10.1002/atr.1425.
[26] Miralinaghi M, Shafahi Y, Anbarani RS. A fuzzy network assignment model based on user equilibrium condition. Sci Iran A 2015;22:2012–23.
[27] Noronha V, Goodchild M. Location-allocation and impulsive shopping: the case of gasoline retailing. Spat. Anal. Locat. Alloc. Model. New York: Van Nostrand Reinhold; 1987. p. 121–36.
[28] Current J, Daskin M, Schilling D. Discrete network location models. Facil. Locat. Theory Appl. Methods. Berlin: Springer-Verlag; 2002. p. 81–118.
[29] Kuby M, Lim S. Location of alternative-fuel stations using the flow-refueling location model and dispersion of candidate sites on arcs. Netw Spat Econ 2007;7:129–52. http://dx.doi.org/10.1007/s11067-006-9003-6.
[30] Lim S, Kuby M. Heuristic algorithms for siting alternative-fuel stations using the flow-refueling location model. Eur J Oper Res 2010;204:51–61. http://dx.doi.org/10.1016/j.ejor.2009.09.032.
[31] Capar I, Kuby M, Leon VJ, Tsai Y-J. An arc cover–path-cover formulation and strategic analysis of alternative-fuel station locations. Eur J Oper Res 2013;227:142–51. http://dx.doi.org/10.1016/j.ejor.2012.11.033.
[32] Ventura JA, Hwang SW, Kweon SJ. A continuous network location problem for a single refueling station on a tree. Comput Oper Res 2015;62:257–65. http://dx.doi.org/10.1016/j.cor.2014.07.017.
[33] Wang Y-W, Lin C-C. Locating road-vehicle refueling stations. Transp Res Part E Logist Transp Rev 2009;45:821–9. http://dx.doi.org/10.1016/j.tre.2009.03.002.
[34] Wang YW, Wang CR. Locating passenger vehicle refueling stations. Transp Res Part E Logist Transp Rev 2010;46:791–801. http://dx.doi.org/10.1016/j.tre.2009.12.001.
[35] Kim J-G, Kuby M. The deviation-flow refueling location model for optimizing a network of refueling stations. Int J Hydrogen Energy 2012;37:5406–20. http://dx.doi.org/10.1016/j.ijhydene.2011.08.108.
[36] Huang Y, Li S, Qian ZS. Optimal deployment of alternative fueling stations on transportation networks considering deviation paths. Netw Spat Econ 2015;15:183–204. http://dx.doi.org/10.1007/s11067-014-9275-1.
[37] Lee Y-G, Kim H-S, Kho S-Y, Lee C. User equilibrium-based location model of rapid charging stations for electric vehicles with batteries that have different states of charge. Transp Res Rec J Transp Res Board 2014;2454:97–106. http://dx.doi.org/10.3141/2454-13.
[38] Shepherd S, Bonsall P, Harrison G. Factors affecting future demand for electric vehicles: a model based study. Transp Policy 2012;20:62–74. http://dx.doi.org/10.1016/j.tranpol.2011.12.006.
[39] Lou Y, Yin Y, Lawphongpanich S. Robust approach to discrete network designs with demand uncertainty. Transp Res Rec J Transp Res Board 2009;2090:86–94. http://dx.doi.org/10.3141/2090-10.
[40] Yin Y, Ieda H. Optimal improvement scheme for network reliability. Transp Res Rec J Transp Res Board 2002;1783:1–6. http://dx.doi.org/10.3141/1783-01.
[41] Lo HK, Tung Y-K. Network with degradable links: capacity analysis and design. Transp Res Part B Methodol 2003;37:345–63. http://dx.doi.org/10.1016/S0191-2615(02)00017-6.
[42] Nie Y (Marco). A class of bush-based algorithms for the traffic assignment problem. Transp Res Part B Methodol 2010;44:73–89. http://dx.doi.org/10.1016/j.trb.2009.06.005.
[43] Boyce D, Ralevic-Dekic B, Bar-Gera H. Convergence of traffic assignments: how much is enough? J Transp Eng 2004;130:49–55. http://dx.doi.org/10.1061/(ASCE)0733-947X(2004)130:1(49).
[44] Pearre NS, Kempton W, Guensler RL, Elango VV. Electric vehicles: how much range is required for a day's driving? Transp Res Part C Emerg Technol 2011;19:1171–84. http://dx.doi.org/10.1016/j.trc.2010.12.010.
[45] Motors Tesla. Tesla motors selects Borg Warner for production of new gearbox for Tesla roadster. 2008. http://ir.teslamotors.com/releasedetail.cfm?releaseid=478009 [Accessed 13 September 2015].

[46] Chung SH, Kwon C. Multi-period planning for electric car charging station locations: a case of Korean expressways. Eur J Oper Res 2015;242:677–87. http://dx.doi.org/10.1016/j.ejor.2014.10.029.
[47] Brooke A, Kendrick D, Meeraus A, Raman R. GAMS: a user's guide. Washington, DC.. 2003.
[48] Bussieck MR, Drud AS. SBB: a new solver for mixed integer nonlinear programming. Duisburg. 2001.
[49] LeBlanc LJ, Morlok EK, Pierskalla WP. An efficient approach to solving the road network equilibrium traffic assignment problem. Transp Res 1975;9:309–18. http://dx.doi.org/10.1016/0041-1647(75)90030-1.
[50] Weinert J, Shaojun L, Ogden J, Jinaxin M. Hydrogen refueling station costs in Shanghai. Int J Hydrogen Energy 2007;32:4089–100. http://dx.doi.org/10.1016/j.ijhydene.2007.05.010.
[51] Ahuja RK, Magnanti TL, Orlin JB. Network flows: theory, algorithms, and applications. Prentice Hall; 1993.
[52] Lou Y, Yin Y, Lawphongpanich S. Robust congestion pricing under boundedly rational user equilibrium. Transp Res Part B Methodol 2010;44:15–28. http://dx.doi.org/10.1016/j.trb.2009.06.004.
[53] Poorzahedy H, Abulghasemi F. Application of ant system to network design problem. Transp (Amst) 2005;32:251–73. http://dx.doi.org/10.1007/s11116-004-8246-7.
[54] Zarrinmehr A, Shafahi Y. Parallelization of the branch-and-bound algorithm in transportation discrete network design. Sci Iran 2016;23:407–19.
[55] Gen M, Cheng R. Genetic algorithms and engineering design. Wiley; 1997.
[56] Aashtiani HZ. The multi-modal traffic assignment problem. 1979.
[57] Zarrinmehr A, Saffarzadeh M, Seyedabrishami S, Nie YM. A path-based greedy algorithm for multi-objective transit routes design with elastic demand. Public Transp 2016;8:261–93. http://dx.doi.org/10.1007/s12469-016-0131-1.
[58] Izadpanah P, Aashtiani HZ. Application of paths information in network design problem. J Transp Eng 2012;138:863–70. http://dx.doi.org/10.1061/(ASCE)TE.1943-5436.0000389.
[59] Zarrinmehr A, Saffarzadeh M, Seyedabrishami S. A local search algorithm for finding optimal transit routes configuration with elastic demand. Int Trans Oper Res 2016. http://dx.doi.org/10.1111/itor.12359.
[60] Aashtiani HZ, Magnanti TL. Equilibria on a congested transportation network. SIAM J Algebr Discret Methods 1981;2:213–26. http://dx.doi.org/10.1137/0602024.