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Incorporating driving range variability in network design for refueling facilities ☆

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ABSTRACT

To stimulate and facilitate the use of alternative-fuel vehicles, it is crucial to have a network of refueling or recharging stations in place that guarantees that vehicles can reach (most of) their destinations without running out of fuel. Because initial investments in these stations are restricted, it is important to choose their locations deliberately. A fast growing stream of literature therefore analyzes the problem of locating refueling or recharging stations. The models proposed in these studies assume that the driving range is fixed, although reality shows that the driving range is highly stochastic. These models thereby misrepresent the actual coverage a network of refueling stations provides to drivers. This paper introduces two problems that do take the stochastic nature of the driving range into account. We first introduce the Expected Flow Refueling Location Problem, which is to maximize the expected number of drivers who can complete their trip without running out of fuel. The Chance Constrained Flow Refueling Location Problem is to maximize the number of drivers for which the probability of running out of fuel is below a certain threshold. We prove the problems to be strongly NP-hard, propose novel mixed-integer programming formulations for these problems, and show how these models can be extended to the case that the driving range varies during a trip. Furthermore, we extensively analyze and compare our models using randomly generated problem instances and a real life case study about the Florida state highway network. Our results show that taking the stochastic nature of the driving range into account can substantially improve network coverage, that optimal solutions are highly robust with respect to data impreciseness, and that the potential gains of stochastic models heavily depend on the driving range distribution. Based on the results, we discuss policy implications.

1. Introduction

The increase in oil prices and concerns about global warming have increasingly motivated the development of alternative-fuel vehicles, which, for instance, use hydrogen, ethanol, biodiesel, natural gas, or electricity as a source of energy. The number of car manufacturers presenting hybrid vehicles is going up and also pure or all-electric vehicles are more and more becoming popular. To facilitate and to stimulate this development, it is crucial to have a network of facilities in place that guarantees that vehicles can reach (most of) their destinations without any problems (i.e., without running out of fuel). Particularly in the first period after the introduction of a new type of alternative-fuel vehicle, investments in these facilities are scarce. There is little opportunity of making money on them, as the pool of potential customers is still relatively small [26].

To overcome this "chicken and egg problem", governments, car manufacturers and other companies make joint efforts to establish an initial network of refueling stations that satisfies the basic needs of potential alternative-fuel vehicle users. For example, Tesla establishes a network of superchargers in Northern-America and Europe, to guarantee that the most important routes are covered sufficiently [27]. As initial budget to place these stations is restricted, it is very important to choose the locations of new stations deliberately.

The problem of choosing the locations of refueling stations has therefore attracted considerable attention in the past few years (see e.g. [20,23,8,9]). These studies model this location problem as a flow coverage problem, where a flow represents a population of electric vehicle (or, more generally, alternative-fuel vehicle) users travelling from the same origin to the same destination. Such flow is defined to be "covered" or "refueled" if the driving distance (or time) between each pair of consecutively passed refueling stations

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does not exceed the driving range of the vehicle. The problem of maximizing the total amount of flow that is refueled is referred to as the Flow Refueling Location Problem (FRLP) and can be solved efficiently by means of standard software [8,23].

The FRLP belongs to the class of facility location problems. Classical facility location problems assume non-moving demand units and a static location of the facilities. This latter assumption is relaxed in dynamic facility location problems, which allow facilities to be relocated (cf. [1]). The assumption of non-moving customers has been relaxed by the class of flow interception facility location problems (FIFLPs), which aim to locate facilities that capture or intercept customers along their origin–destination paths see e.g. [13,5]. Examples of flow interception problems include the positioning of billboards [3], roadside healthcare facilities [10] and refueling locations (e.g., the FRLP). Berman and Krass [4] extend the flow interception problem by accounting for competition among different facilities.

Whereas these classical flow interception problems assume that customers follow certain pre-planned paths, Kim and Kuby [18] formulate the location problem in which drivers are willing to deviate from their preferred paths to refuel their vehicles. This problem is referred to as the *deviation* flow refueling location problem. Yıldız et al. [29] propose a branch and price approach to solve this problem, which significantly reduces the computation time. Finally, whereas the FRLP and the deviation FRLP mainly focus on enabling long-distance trips, Kang and Recker [16] optimize locations with respect to short-distance traffic, for which the driving range is assumed to be of no limitation. Instead, the authors propose models to locate the facilities based on household scheduling and routing considerations.

The flow refueling location problems discussed so far implicitly assume that the driving range of a vehicle is fixed and known in advance. However, reality shows that the driving range is highly variable. For instance, it is dependent on the age of the battery, the temperature, the amount of traffic on the road, and the driving style [12,24,11]. Therefore, regarding the driving range as fixed can significantly misrepresent the coverage level provided by a network of refueling stations, and potentially lead to location choices that are far from optimal in reality. Lee et al. [22] make a first attempt to include stochasticity of the driving range into the location problem, by assuming a randomly distributed battery load at the beginning of a trip from origin to destination. The authors, however, unrealistically assume that the driving range is sufficient to cover all origin-destination combinations, such that recharging is needed at most once during a trip. Simulated annealing is used to solve the location problem for a small network.

In this paper, we investigate two ways to incorporate the stochastic nature of the vehicle driving range into the problem of locating refueling stations. We first propose a novel formulation of the FRLP, which contains the driving range explicitly as a parameter (in contrast with existing formulations). Using this formulation as a starting point, we first introduce and model the Expected Flow Refueling Location Problem, which is to maximize the expected number of drivers who can complete their trip without running out of fuel. Although this model provides a natural way to deal with stochasticity, it does not consider the coverage levels provided to each of the flows separately. As a consequence, it prefers to provide two equally sized flows with 51% coverage over providing one flow with 100% coverage. This might be easily justifiable in the context of hybrid (electric) vehicles, which can switch to a different power source when the primary source is exhausted. However, since drivers of, for instance, pure electric vehicles or hydrogen vehicles will strongly dislike the large probability of running out of fuel, this solution will be far from optimal in their context. We therefore also introduce and model the Chance Constrained Flow Refueling Location Problem, which is to maximize the number of drivers for which the probability of completing their trip without of running out of fuel is at least $1-\alpha$. We numerically analyze these models using randomly generated networks (see [8]) and a real life case study on the Florida state highway network (see [21,9]).

The remainder of this paper is organized as follows. Section 2 describes our novel formulation of the FRLP. The stochastic model formulations are introduced in Sections 3 and 4 describe our numerical results. Finally, in Section 5 we draw conclusions and state opportunities for future research.

2. Novel formulation of the Flow Refueling Location Problem (FRLP)

The Flow Refueling Location Problem can be described as follows. Consider a network $G(L,E)$ where L denotes a set of locations and E a set of arcs between these locations. The set of locations L is the union of the following three sets: the set of potential facility locations, K, the set of origins, O, and the set of destinations, D. Consider a collection of drivers who travel along this network. In line with the literature [20,8] we use the term flow to refer to the subset of drivers that travels from the same origin to the same destination along the same path. Let F denote the set of all the flows and let O_f and D_f denote respectively the origin and destination of the drivers along flow $f \in F$. The path travelled by the drivers in flow f is an ordered sequence of edges $e \in E$ connecting the following vertices: the start vertex $O_f \in O$, an ordered subset of potential facility locations, $K_f \subseteq K$, and the end vertex, $D_f \in D$. The volume of flow f, i.e., the number of drivers that travels from O_f to D_f, is denoted by v_f. The vehicles have a driving range of R (miles/kilometers), and can be refueled/recharged at refueling facilities along their route. We consider a flow to be *covered* if vehicles can travel from their origin to their destination and back to their origin without running out of fuel. Note that this is the case if and only if the driving range exceeds the travel distance between successive refueling facilities along such trip. The objective of the FRLP is to locate p facilities in the network, so as to maximize the number of drivers covered.

Existing models for the FRLP include the driving range restriction implicitly by representing the coverage of a flow or arc by means of binary parameters [20,8,9,23]. We propose a new MIP formulation that explicitly contains the driving range. Before we propose our model, let us introduce some notations. We use the binary decision variable x_k to indicate whether a facility is placed at potential facility location k ($x_k = 1$) or not ($x_k = 0$). For the sake of simplicity, we assume that there are currently no facilities in the network. The model can easily be adapted in the case that there are. Furthermore, we use auxiliary variables y_f to indicate whether flow f is covered (i.e., refueled: $y_f = 1$) or not ($y_f = 0$).

In what follows we will use a slightly different vector of vertices to represent a path:

$$\pi_f = [\pi_f(1), \pi_f(2), \ldots, \pi_f(n-1), \pi_f(n)]$$

Here, $\pi_f(1)$ and $\pi_f(n)$ represent the origin vertex O_f and the destination vertex D_f, respectively. The vector $[\pi_f(2), \ldots, \pi_f(n-1)]$ is the sequence of locations $k \in K_f$ with a new facility passed during a trip from O_f to D_f. We call these locations new facility locations. Hence, this representation does not necessarily include all $k \in K_f$. Note that π_f depends on the decision variables x_k for all $k \in K_f$, because these variables determine the new facility locations. We make the following assumption about this path: