Computers & Industrial Engineering 70 (2014) 195–204

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

A hybrid heuristic approach to the problem of the location of vehicle charging stations

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ARTICLE INFO

Article history:
Received 16 March 2013
Received in revised form 11 November 2013
Accepted 1 February 2014
Available online 10 February 2014

Keywords:
Charging stations
Location
Heuristic approach
Mixed-integer programming

ABSTRACT

In order to reduce the negative impact of fuel-powered vehicles on the environment, the use of alternative-fuel vehicles (AFVs), which produce far less pollution than traditional fuel-powered vehicles, is being introduced in many countries around the world. However, compared to the fuel-powered vehicles, AFVs such as electric vehicles require frequent recharging of their electrical energy storages (batteries), which results in a short vehicle driving range. Thus, AFV users who want to travel from home to a terminal location and back again must consider whether their AFVs can be recharged on the way. One of the approaches to solve this problem is to install alternative fuel charging stations on suitable locations to provide recharging services. However, when the budget is limited, the selection of locations and the types of alternative fuel charging stations becomes a decision problem, since it will directly affect the number of potential AFV users that can be served. This paper develops a mixed-integer programming model to address this problem and to maximize the number of people who can complete round-trip itineraries. A hybrid heuristic approach is proposed to solve this model. Numerical results show that the proposed heuristic approach only requires a small amount of CPU time to attain confident solutions.

1. Introduction

Transport services play an important role in daily life. These services include: (1) land transportation, using automobiles, bikes, trains, etc., (2) water transportation, using ships, boats, barges, steamers, etc., and (3) air transportation, using air-craft, and airships. These services may vary in terms of the distance covered, vehicle types used, routes and timetables. Of the land transport options, fossil fuel-powered vehicles are usually used for transport in urban areas, or to and from the suburbs to population centers. These services are often parts of a network, centered on an urban center, or across a city, and usually involve a fixed route and schedule. The use of fuel-powered vehicles produces some gases such as carbon dioxide, nitrogen oxides, ozone and microscopic particulate matters. These waste gases cause air pollution and harm our health and the environment. As reported by the WRI (2006), 65% of global CO2 emissions come from energy use, and 21% comes from transportation, which is dependent on fossil fuels. Thus, decreasing CO2 emissions has been viewed as an important policy around the world, from USA to European Union and to China and Japan in Asia (Lund & Clark, 2008).

Since electric-powered vehicles produce far less pollution than traditional fuel-powered vehicles, they seem not to cause harm to our environment or public health. Thus, electric-powered vehicles are called as partial zero-emission vehicles, even though they still emit pollutants. Accordingly, many countries have begun to introduce electrically powered vehicles in their public transport services, to reduce the gaseous emissions from fossil fuel-powered vehicles. With all the efforts expended on green initiatives and protecting the environment, it is little wonder that electric-powered vehicles have become a popular alternative to traditional fossil fuel-powered vehicles. However, they still have some limitations (Electric vehicle site, 2011). One of the limitations is their limited driving range. Thus, users must consider how many miles can be covered before a recharge is needed. There is no doubt that this restricts their use as transport tools. So for electric-powered vehicles to be practical, the provision of enough alternative fuel vehicle stations is an important issue. This study deals with the problem of refueling locations for alternative-fuel vehicles.

The refueling location problem is a facility location problem. The key questions commonly faced by facility planners include: (1) the number of facilities, (2) the locations of these facilities and (3) the types of facilities (in terms of size, product variety

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http://dx.doi.org/10.1016/j.cie.2014.02.001
0360-8352/

and other design aspects). Aboolian, Berman, and Krass (2007) dealt with the competitive facility location and design problem (CFLDP) by simultaneously optimizing the locations and designs of a set of new facilities under a budget constraint and pre-existing competitive facilities. They developed a solution with an adjustable error bound. Frick, Axhausen, Carle, and Wokaun (2007) investigated the problem of the placement of stations for compressed natural gas in Switzerland. Two scenarios for possible distributions of these stations were studied. In the first case, the scoring function was given in terms of the filling station owners' investment costs and their attractiveness for CNG car drivers. In the second case, the scoring function approximated the results of a social cost-benefit analysis, which focused on the investment costs as well as the environmental and user benefits. The results from the two cases show that the social and commercial outcome of an investment can be quite different, depending on the optimization strategy pursued.

Most location models focus on either minimizing the average cost of travel (the median problem) or minimizing the maximum cost of travel (the center problem). A large number of these models assume that the demand for service originates from the nodes of the network. In other words, this assumption implies that customers make a dedicated trip to a specific facility to obtain a service. One popular model for this problem is the p-median model. The p-median model locates a given number of facilities on a network and allocates demand nodes to each facility, in order to minimize the total weighted distance traveled. Nicholas, Handy, and Sperling (2004) developed a GIS model for the location of hydrogen fuel stations in Sacramento County, California, under the assumption that the existing petrol infrastructure is strongly related to the required hydrogen infrastructure of the future. A greedy algorithm, adding two stations at a time, was used for the model. Lin, Ogden, Fan, and Chen (2008) developed a fuel-travel-back approach to deal with the station-siting problem. The only data required for this approach are the distribution of traveled vehicle miles. Their proposed fuel-travel-back problem is treated as a typical transportation problem, which can be solved by a mix-integer-programming model. Wang (2007) developed a recreation-oriented facility location model to economically set the slow recharging stations at scenic spots, for electric scooters traveling on a single O–D (origin–destination) trip using multi-stop refueling. Later, Wang (2008a) extended this model to a case with multiple O–D trips, under the assumption that the length of a trip was also within the vehicle range. The purpose of his model was to optimally site the refueling stations to cover overall passing flows on the paths of interest, instead of the O–D flow data. Wang (2008b) proposed a simulation model to deal with a deterministic location problem for the identification and assessment of the service capacity and performance of a tourism/recreation-oriented electric scooter recharging system with random demands.

In practice, retail facilities such as gas stations and convenience stores also try to capture flow-by customers. In other words, in urban or intra-city travel, demand in a network is fixed-point type and flow-type (Goodchild & Noronha, 1987; Hodgson, 1990; Hodgson & Rosing, 1992). One popular model for the optimal location of alternative-fuel stations to capture flow-by customers is the flow-refueling model, proposed by Hodgson (1990) and Berman, Larson, and Fouska (1992) who referred to it as a flow-intercepting model. In flow-capturing location models (FCLM), demand consists of paths through a network, instead of points of origin for trips to the facility and back. These models are structurally similar to the maximum-coverage problems, which locate a given number of facilities in a network, so as to maximize the traffic flow passing by the facilities. These models are used to locate discretionary facilities, such as ATMs, convenience stores and fast food outlets, at which people stop on their way to somewhere else, rather than making a special trip from home to the facility and back (Kuby et al., 2009). Berman, Hodgson, and Krass (1995) surveyed the works on the optimal facility location, based mainly on flow-by customer traffic. These models were firstly introduced by Berman et al. (1992) and Hodgson (1990). They assume that customers who make an origin to destination trip (for example, from home to the work place) for a certain purpose may also obtain other services if they pass through other facilities. Averbakh and Berman (1996) developed two flow-capture models to address two-location problems. The first problem was the minimization of the number of facilities required to ensure the maximum level of consumption. The second problem was to maximize consumption subject to a given number of facilities. The assumption that facilities only rely on pre-existing customer flows is made in most of the flow interception models, and the assumption that facilities rely exclusively on dedicated trips is made in most of the traditional median and center models.

Many real-life retail facilities rely not only on special trip purchases, but also on intercepting passing customers. Thus, several hybrid models have incorporated these two cases. Berman and Krass (1998) studied a facility location problem in which demand came from both customers with special-purpose trips and customers passing by a facility while en route to another destination on the network. They developed a branch-and-bound scheme and a tight upper bound for their model. Berman and Krass (2002) proposed a spatial interaction model to investigate the competitive facility location problem with considering the effects of market expansion and cannibalization. Hodgson (1990) and Berman et al. (1992) explored the flow capturing location–allocation problem with the purpose of capturing most of the flow-type demand (short distance trips via one-stop refueling) on the paths under budget restrictions. Kuby and Lim (2005) extended the problem of Hodgson (1990) and Berman et al. (1992) to the flow refueling location problem by considering the limited driving range of alternative-fuel vehicles (AFV) when undertaking long-distance trips and using multi-stop refueling.

The FCLM assumes that a single facility on a path is sufficient to serve the demands. However, even though a single facility is located on a path, the single station may not be enough to complete a long-range trip, due to limited driving range. Accordingly, one or more stations must be located on a path to refuel a vehicle so that it does not run out of fuel. Thus, the flow-refueling location model (FRLM), which considers the distance of a path, was proposed to extend the flow-capturing model proposed by Hodgson (1990) and by Berman et al. (1992). FRLM is a path-based demand model that locates a given number of stations in order to maximize the number of trips on the shortest paths that can be refueled. The purpose of the FRLM models is to locate a given number of refueling stations so that the maximum volume of traffic flows traveling on their shortest paths from origins to destinations can be refueled. In the flow-refueling location model, instead of nodes, demand covered is in terms of O–D pairs. Kuby and Lim (2005) dealt with the optimal location for fueling stations. However, their work does not set out to serve origin–destination demands. Kuby and Lim (2007) developed a FRLM model to extend the flow-capturing/intercepting problem by incorporating a driving limitation. Lim and Kuby (2010) presented a flow-refueling location model and developed a genetic algorithm to find the optimal station locations for alternative-fuels, so as to maximize the flow that can be refueled in a given number of facilities. Wang and Wang (2010) developed a mixed integer programming model to study a refueling station location problem for an emerging and/or monopolistic automotive market of alternative fuel vehicles. The objective function of their model minimizes the facility cost and maximizes the population coverage. Upchurch and Kuby (2010) compared the p-median and flow-refueling models for alternative-fuel location problem. Wang and Wang (2010) assumed that an AFV on an outbound trip could refuel at home. As a variation of model of Wang and Wang (2010), this paper allows an AFV to refuel a certain amount at the initial station and allows multiple refueling station types under budget restrictions.

The previous flow-based models assume that demand covered is in terms of O–D pairs. That is, a demand for a trip is covered if the trip from a home location to a specific destination can be completed with single or multiple stops for refueling. This type of trip can be considered as either an outbound trip, from home to a destination, or an inbound trip, from a destination back to home. It is noteworthy that most people who make travel itineraries to a destination return home again. That is, a travel itinerary is usually a round-trip plan, which consists of an outbound trip and an inbound trip. Thus, a travel itinerary cannot be completed if either the inbound trip or the outbound trip, or both, does not occur. Accordingly, round-trip demands are covered if and only if both the outbound and the inbound trips can be completed with multi-stop refueling. In their models, Wang and Lin (2009) and Wang and Wang (2010) followed three vehicle logics to discuss the location of refueling stations. Of these three logics, the vehicle refueling logic states that the remaining fuel at a node is equal to the remaining fuel, plus the refueling at a prior node, minus the fuel consumption for the distance traveled between. Using this logic, they developed models to economically allocate refueling stations to serve limited-range AFVs traveling on predetermined O–D trips. They also assumed that the combinations of O–D trips and AFV types are predetermined. In addition, the constraints in their models do not provide the refueling information for each combination of O–D trip and AFV type.

This study proposes an O–D trip based model that extends the model of Wang and Wang (2010). In our model, the O–D trips and the types of AFVs used on the available O–D trips are control variables and the type of station can be selected. This variation allows the decision-maker to select suitable O–D trips from a number of possible O–D trips by determining the location of refueling stations so as to serve the maximum population under budget constraints.

Moreover, most of the previous models assume that a demand node is covered even if the demand node is within the coverage distance of another node where a refueling station is established. However, from a convenience point of view, this leads to the situation wherein an AFV may not travel from its departure node on the shortest-path to its destination. Therefore, the proposed model assumes that an AFV must refuel at a node on its shortest-path. In addition, previous works usually used commercial software to solve the refueling station location problem. Commercial software can solve the considered problems optimally for suitable size problems. However, due to the exponential increase in CPU time, it cannot solve these problems optimally, or even produce a feasible solution within a reasonable time limit for larger scale problems. In order to overcome this difficulty, in this paper, we will propose a hybrid heuristic approach to solve the proposed problem. In short, in this paper, we will proposes a hybrid heuristic approach for the O–D trip based model which simultaneously combines the locations and types of recharging stations. The objective of this considered problem is to find the optimal O–D trips and AFV types of stations such that the population coverage is maximized.

2. Model assumptions and formulation

The proposed model aims to maximize the coverage of the round-trip population on a network by determining the locations and types of recharging stations and the AFVs' recharging quantity at each recharging station. Consider a traffic network with N nodes or locations, in which location i has population p_i. Since, in general, not all people are AFV users, it is assumed that α percent of population are potential AFV users in each location. That is, in location i, the potential AFV population is estimated to be αp_i. A round trip from node-i to destination node-j and back from destination node-j to node-i again is denoted as O–D trip-(i,j). Assume that for any O–D trip, an AFV travels from its origin node to its destination node and back from its destination node to the origin node along the shortest path between the nodes considered. An O–D trip is not restricted to a special purpose trip and can also include passing purpose trips. Let itinerary-(m,i,j) denote the journey type wherein a type-m AFV travels on O–D trip-(i,j) and f_{ij}^m be the population for itinerary-(m,i,j). Then, the total number of potential AFV population can be expressed as $\sum_{j=1,j\neq i}^{N}\sum_{m=1}^{M} f_{ij}^m = \alpha p_i$ where M is the total number of AFV types. Let β_m and e_m be the recharging capacity and the fuel consumed per unit distance for AFV type-m, respectively. Then, the driving range of AFV type-m can be expressed as β_m/e_m.

For O–D trip (i,j), let the first-node be the original node of the O–D trip and the q_{ij}th visiting node be the destination node. Then, the total number of nodes on O–D trip (i,j) is $2q_{ij}-1$. Fig. 1 shows the visiting sequence of O–D trip (i,j). In this figure, node $h_{ij}(n), n = 1,\ldots,2q_{ij}-1$, represents the nth visiting node on O–D trip (i,j). Herein, $h_{ij}(1)$ and $h_{ij}(2q_{ij}-1)$ represent the original node, i, and $h_{ij}(q_{ij})$ represents the destination node, j. Symbol $s_{ij}(n)$ represents the distance between node, $h_{ij}(n)$, and node, $h_{ij}(n+1)$ fuel remaining in type-m AFV at node-$h_{ij}(n)$ of O–D trip (i,j) and let $R_{ij}^m(n)$ be the fuel added to type-m AFV at site-$h_{ij}(n)$ on O–D trip

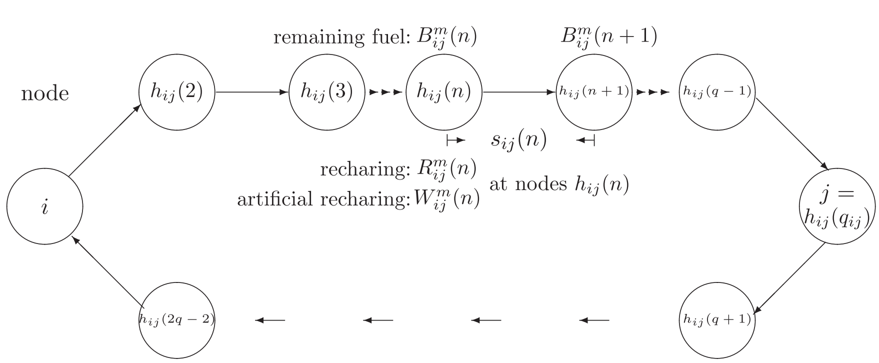

Fig. 1. Traveling example for O–D trip (i, j).

(i,j). In addition, for O–D trip (i,j), if a type-m AFV can complete the trip with single or multiple stops for recharging, then this trip is a feasible (m,i,j) itinerary. In this case, $B^{tm}_{ij}(n+1)$ and $B^{tm}_{ij}(n)$ have the relationship $B^{tm}_{ij}(n+1) = B^{tm}_{ij}(n) + R^{1m}_{ij}(n) - s^{t}_{ij}(n)e_m$.

However, if itinerary (m,i,j) is infeasible, type-m AFV must not have sufficient fuel to complete the trip on at least one inter-node journey. To develop our model, let $W^m_{ij}(n)$ denote type-m AFV's artificial refueling amount (insufficient fuel amount) on the inter-city journey from node-$h_{ij}(n)$ to node-$h_{ij}(n+1)$ on O–D trip (i,j). Then, for an infeasible (m,i,j) itinerary, $B^m_{ij}(n+1)$ and $B^{tm}_{ij}(n)$ can be expressed as $B^m_{ij}(n+1) = B^{tm}_{ij}(n) + W^m_{ij}(n) - s_{ij}(n)e_m$. The variables for the artificial recharging amounts, $W^m_{ij}(n)$s, indicate whether an O–D trip is a feasible itinerary or not. That is, for any passed node, $h_{ij}(n)$, if there exists a $W^m_{ij}(n)$ such that $W^m_{ij}(n) > 0$, itinerary (m,i,j) is not a feasible itinerary. To distinguish whether itinerary-(m,i,j) is feasible or not, let the symbol, z^m_{ij}, be a binary variable and let $z^m_{ij} = 1$ if itinerary-(m,i,j) is feasible and zero otherwise.

By considering the budget restriction, the purpose is to capture as many AFV users as possible through the following decisions: (1) For each node, if there should establish a recharging station and if yes, what kind of recharging station and (2) for each type of AFV on each O–D trip, how much to refuel at each established recharging station. The results also reveal the following: (1) the feasible O–D trips, (2) the types of AVFs traveling on each feasible itinerary, (3) the station for recharging of each type of AFV on each feasible itinerary and (4) the recharging amount. The notation is summarized as follows and the formulation of the problem is addressed thereafter.

Notation

i, j, n	a node or location
H	the available budget
K	total number of station types
M	total number of AFV types
N	total number of nodes or locations
(i,j)	a round trip from node-i to destination node-j and back from destination node-j to node-i again
(m,i,j)	the journey type wherein a type-m AFV travels on a O–D trip-(i,j)
β_m	the recharging capacity for AFV type-m
c_{ik}	the cost of locating a type-k station at node i
d_{ij}	the traveling distance between nodes i and j
e_m	the fuel consumed per unit distance for AFV type-m
f^m_{ij}	the population using type-m AFV to make O–D trip (i,j)
G_k	the capacity of type-k station
$h_{ij}(n)$	the nth node on O–D trip (i,j)
$s_{ij}(n)$	the distance between node, $h_{ij}(n)$, and node, $h_{ij}(n+1)$
L	a large positive integer

Decision variables

$B^m_{ij}(n)$	the fuel remaining in type-m AFV at node-$h_{ij}(n)$ on itinerary (i,j)
$R^m_{ij}(n)$	the fuel added to type-m AFV at site-$h_{ij}(n)$ on itinerary, (i,j)
$W^m_{ij}(n)$	type-m AFV's artificial recharging amount (insufficient fuel amount) on the inter-city journey from node-$h_{ij}(n)$ to node-$h_{ij}(n+1)$ on O–D trip (i,j)
x_{ik}	1 if a type-k station is located at node i, and zero otherwise
z^m_{ij}	1 if itinerary-(m,i,j) is feasible and zero otherwise

Formulation

$$\max_{\mathbf{x}} \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{N} f^m_{ij} z^m_{ij}, \tag{1}$$

$$\text{s.t.} \quad \sum_{i=1}^{N}\sum_{k=1}^{K} c_{ik}x_{ik} \leqslant H, \tag{2}$$

$$B^m_{ij}(n+1) = B^m_{ij}(n) + R^m_{ij}(n) + W^m_{ij}(n) - s_{ij}(n)e_m,$$
$$\forall i,j,m,n < 2q_{ij}-1, \tag{3}$$

$$\left(1 - z^m_{ij}\right)L \geqslant W^m_{ij}(n), \quad \forall i,j,m,n \leqslant 2q_{ij}-1, \tag{4}$$

$$B^m_{ij}(n) \leqslant \beta^m, \quad \forall i,j,m,n \leqslant 2q_{ij}-1, \tag{5}$$

$$R^m_{ij}(n) \leqslant \beta^m - B^m_{ij}(n), \quad \forall i,j,m,n \leqslant 2q_{ij}-1, \tag{6}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{m=1}^{M}\sum_{k=1,h^k_{ij}=n}^{2q_{ij}-1} R^m_{ij}(k) \leqslant \sum_{k=1}^{K} G_k x_{nk}, \quad \forall i,j,m, \tag{7}$$

$$\sum_{k=1}^{K} x_{ik} \leqslant 1, \quad \forall i, \tag{8}$$

$$x_{ik}, z^m_{ij} \in \{0,1\}, \quad i,j,m, \quad \forall i,j,k,m, \tag{9}$$

$$B^m_{ij}(n), R^m_{ij}(n) \geqslant 0, \quad \forall i,j,m,n. \tag{10}$$

Eq. (1) is the objective function. Eq. (2) is the budget constraint. Eq. (3) ensures that the remaining fuel at a station is equal to the remaining fuel plus recharging at the prior station minus the fuel consumption during the link traveled. Eq. (4) shows that an O–D trip is not a feasible itinerary if there is an insufficient fuel amount on any one of the inter-city journey on the O–D trip. Eq. (5) ensures that the remaining fuel at a station is no larger than its recharging capacity. Eq. (6) shows that the amount of recharging at any station must be less than or equal to the recharging capacity minus the amount of fuel remaining at that station. Eq. (7) is the supply limitation for a facility. Eq. (8) ensures that at most one facility is setup for each candidate location. Eq. (9) is the constraint for binary variables. Eq. (10) is constraint for non-negative variables.

Some constraints in the model of Wang and Wang (2010) are similar to those of our model. The main difference includes the followings. In their model, demand of a node is satisfied if there is at least one station located within its coverage distance. In our model, demands are satisfied if only if their round-trip itinerary can be completed. In addition, constraint (3) extends the vehicle refueling logic constraint in their model to a case wherein all passed nodes on an itinerary are considered. Thus, according to the stations sited, constraints (3) and (4) of our model can confirm the feasible itineraries and infeasible itineraries. For a feasible itinerary, our model can provide the information of locations and quantities to refuel. For an infeasible itinerary, our model can provide the information of locations and insufficient quantities to refuel when we want to have a certain type of AFV on the itinerary. Moreover, the purpose of our model is to maximize the coverage of the round-trip population on a network within budget limit by determining the locations and types of recharging station and AFVs' recharging quantity at each recharging station.

3. A solution procedure

The considered problem is a combinatorial optimization problem. Optimally solving this problem is computationally impossible for large-scale problems. Thus, a hybrid heuristic approach (HGA) is developed to obtain a compromised solution within a reasonable CPU time in this paper. The HGA approach is an iterative method, which incorporates the concept of a genetic algorithm. As known, genetic algorithm (GA) is an iterative optimization procedure that mimics the process of natural evolution. It can generate exact or approximate solutions using techniques inspired by evolutionary biology, such as inheritance, mutation, selection, and crossover. For details, readers are referred to two textbooks by Onwubolu and Babu (2004, chap. 2) and Michalewicz (1996). Next, for shortening this paragraph, we only address the key point of procedures for HGA as follows:

(A) Initial population:

In this step, an initial population of size Pop_{size} is randomly generated.

A generic chromosome composes $2S_{max}$ facility location variables and $2S_{max}$ facility type variables, where S_{max} is the maximum number of facilities that can be established. The value of S_{max} is determined by the formula, $S_{max} = H/c_{min}$ where $c_{min} = \min\{c_{ik},\ \forall i,k\}$. The lower bound and the upper bound of the facility location variables and the facility type variables are set within the range, $[1, N_{max}]$ and $[1, K_{max}]$, respectively. A generic chromosome V is coded as a binary string, $V = (A, T)$ where $A = \{a_{11}, a_{12}, \ldots, a_{1,L_1}\}$ represents the decisions associated with facility locations and $T = \{t_{11}, t_{12}, \ldots, t_{1,L_2}\}$ represents the decisions associated with facility types. In addition, L_1 is the gene length of the $2S_{max}$ facility location variables and L_2 is the gene length of the $2S_{max}$ facility type variables.

An example: In this example, we set the values of N_{max}, H, K_{max} and c_{ik} at $N_{max} = 8$, H = 2,500,000, $K_{max} = 4$ and c_{ik} = 1,125,000 + 250,000$(k-1)$ to illustrate how to represent a chromosome. Since S_{max} = 2,500,000/1,125,000 = 2, we set four facility location variables and four facility type variables in a chromosome. The gene length for each location variable and each facility type variable are 3 and 2, respectively. Thus, a chromosome, V, consists of 16 genes, in which the first $L_1 = 4 \times 3 = 12$ genes represent the facility location genes, A, and the remaining $L_2 = 8$ genes represent the facility type genes, T. Chormosomes V_1^1 and V_2^1 in Table 1 are two encoding examples.

(B) Genetic operators:

Once an initial population has been formed, four genetic operators, namely the cloning operator, parent selection, crossover operator and mutation operator repeatedly performed until a stopping criterion is satisfied. The stop criteria are that the maximum number of iterations, $Iter_{max}$, is reached or a converged solution is achieved. An elitism strategy and the roulette-wheel selection are used in cloning operator and parent selection, respectively. The four operators follow the standard genetic operators.

Crossover operator: The crossover operator for the facility location genes and the facility type genes are separately performed. In this step, two individuals are sequentially chosen from the mating pool for crossover. Suppose that a crossover operation is performed on chromosomes V_1^1 and V_2^1 in Table 1. To perform crossover, we randomly generate two integer numbers pos_1 and pos_2 within $[1, L_1]$ and $[1, L_2]$, respectively. Numbers pos_1 and pos_2 indicate the crossing points of the facility location genes and the facility type genes, respectively. The single crossover operator is used to perform crossover. Suppose that the two inter-gene crossing points are $pos_1 = 4$ and $pos_2 = 2$. Then, the two candidate offsprings generated from their parents are $V_1^{2'}$ and $V_2^{2'}$ (see Table 1).

Table 1
An example of encoding and crossover operators.

Chromosome	Variable	
	Location variable	Type variable
V_1^1	0 1 0 1| 1 1 0 1 0 0 0 0	0 1| 0 0 0 0 0 1
V_2^1	0 1 1 1| 0 1 0 1 0 0 0 0	1 0| 1 0 1 0 0 1
$V_2^{1'}$	0 1 0 1| 0 1 0 1 0 0 0 0	0 1| 1 0 1 0 0 1
$V_2^{2'}$	0 1 1 1| 1 1 0 1 0 0 0 0	1 0| 0 0 0 0 0 1

Mutation operator: For each crossed individual, we generate a real number, r, within $[0, 1]$ and an integer random number pos within $[0, L_1 + L_2]$. If $r < \rho$, we replace the value at posth bit with 1 minus its current value.

Decoding operator: Note that each binary chromosome is decoded into an integer vector, $U(a_1, \ldots, a_{2S_{max}}, t_1, \ldots, t_{2S_{max}})$, where a_j and $t_j, j = 1 \cdots 2S_{max}$ are the decoded values of binary vectors A and T, respectively. Consider the previous example in Table 1. The chromosome of parent 1 V_1^1 is decoded as $U_1^1 = (a_1, .., a_4, t_1, .., t_4) = (3\ 8\ 3\ 1,\ 2\ 1\ 1\ 2)$.

(C) Fitness:

To evaluate the fitness of each chromosome, the values of the decision variables x_{ik}s, $B_{ij}^m(n), R_{ij}^m(n)$ and Z_{ij}^m must be determined. Below, we use steps (a) and (b) to determine these values.

(a) The determination of decision variables x_{ik}:

For the budget constraint in Eq. (2) not to be violated, we let $x_{ik} = 0$ for all i, k, except for $x_{a_j,t_j} = 1$ for $j \leqslant j^*$ where j^* is determined by

$$j^* = \max\left\{ s \,\middle|\, \sum_{j=1}^{s} x_{a_j,t_j} c_{a_j,t_j} \leqslant H \right\}. \tag{11}$$

According to the decoding results, there may exist a j such that $x_{a_j,t_j} = 1$ and exist some $k > j$ such that $x_{a_k,t_k} = 1$ and $a_k = a_j$. This result violates constraint (8) since more than one recharging station is set in location a_j. To avoid such a situation, for $k > j$, we let $x_{a_k,t_k} = 0$ for all $a_k = a_j$ if $x_{a_j,t_j} = 1$. This modification ensures that constraint (8) is satisfied.

Using the previous example, the binary codes of V_1^1 in Table 1 are decoded into integer codes, $U = (a_1, \ldots, a_4, t_1, \ldots, t_4) = (3, 8, 3, 1, 2, 1, 1, 2)$. In this case, we have $j^* = 2$ and we conclude that $x_{ik} = 0$ for all i, k except for $x_{3,2} = 1$ and $x_{8,1} = 1$. That is, locations 3 and 8 are allocated facilities with types 2 and 1, respectively.

(b) The determination of decision variables $B_{ij}^m(n), R_{ij}^m(n)$ and Z_{ij}^m:

For each chromosome, we let set ω be the set $\{i | x_{ik} = 1\ \forall i\}$, and let $y_{ij}^m(n)$ be a binary variable such that $y_{ij}^m(n) = 1$ for $n \in \omega$ and zero otherwise. The binary variable $y_{ij}^m(n)$ is used to judge whether or not type-m AFV is refueled at site-$h_{ij}(n)$ on itinerary, (i, j). For each O–D trip (i, j), we use the following procedure to determine the values of $B_{ij}^m(n), R_{ij}^m(n)$ and Z_{ij}^m.

1. Let $B_{ij}^m(1) = \beta^m$ and $Z_{ij}^m = 1$ for all i, j, m.
2. For $n \leqslant 2q_{ij} - 1$, let $R_{ij}^m(n) = y_{ij}^m(n)(\beta^m - B_{ij}^m(n))$.
3. For $n < 2q_{ij} - 1$, sequentially determine $w_{ij}^m(n)$ according to the following rule:
   3.1 let $B_{ij}^m(n+1) = B_{ij}^m(n) + R_{ij}^m(n) - s_{ij}(n)e_m$,
   3.2 let $w_{ij}^m(n) = 0$ if $B_{ij}^m(n+1) \geqslant 0$ and let $w_{ij}^m(n) = -B_{ij}^m(n+1)$ if $B_{ij}^m(n+1) < 0$,
   3.3 let $B_{ij}^m(n+1) = 0$ and $Z_{ij}^m = 0$ if $w_{ij}^m(n) > 0$.

By substituting the values of Z_{ij}^ms into (1), the objective value is obtained. Until this step, all constraints, except for constraint (7), are satisfied. Some penalties are incurred for the violation of constraint (7). Finally, the sum of the objective value and penalties is the fitness of the chromosome.

(D) Solution update:
The solution is updated if the result obtained in step 3 is feasible and larger than the current best objective value.
(E) Stopping criteria:
The approach executes steps (b)–(d) until the stop criterion is matched.
(F) Output

4. Numerical results and discussions

In this section, we illustrate the considered problem by one example, test the performance of the presented heuristic algorithm and discuss the computational results for test problems.

4.1. Test problems

In the experiment, six types of problem sizes, in terms of the number of locations, the number of types of AFVs and the number of available facility types, are considered. The combinations of (N, M, K) are $(15, 1, 1), (20, 1, 1), (20, 1, 2), (40, 1, 2), (51, 2, 1)$ and $(80, 1, 1)$ for problem types 1–6, respectively. For each problem type, ten instances were generated. The parameters for all instances in all problem types were generated as follows. First, let symbol η_{ij} denote the distance between two adjacent nodes, i and j. Then, d_{ij} is equal to η_{ij} when nodes, i and j, are adjacent. For problem types 1–4 and 6, the values of η_{ij}s and p_is were randomly generated. However, for problem type 5, these values are set the same as those for the Taiwanese road network, used by Wang and Lin (2009). For problem types 1–4 and 6, the simulated values of η_{ij}s for all adjacent nodes and the population of p_is in a network with $N = 80$ nodes are shown in Tables 2 and 3, respectively.

Because of the difficulty of identifying the practical routes or paths being traveled, this study assumes that all O–D trips are traveled on the shortest path. The Floyd algorithm, proposed by Daskin (1995), was used to obtain the overall shortest paths and then the values of d_{ij}s and $s_{ij}(n)$s. In each location, the potential AFV population for a node is assumed to be $\alpha = 30$ percent of people at that location. Thus, the potential population for each (m, i, j) itinerary is computed to be $f_{ij}^m = \alpha p_i d_{ij} \Big/ \left(M \sum_{j=1}^{N} d_{ij}\right)$. The remaining parameters, except for the budget of H, are assumed to be $c_{ik} = 1{,}125{,}000 + 225{,}000(k-1)$, $e_m = 0.25 + 0.05(m-1)$, $G_k = 1{,}000{,}000 + 250{,}000(k-1)$ and $\beta_m = 15 + 10m$. Budget H is assumed to be $H = 1{,}125{,}000\rho$, in which the values of ρ are shown in Tables 6–12.

The proposed HGA was coded in Visual C++ 6.0 programming language and implemented on an Intel Core 2 Duo personal computer equipped with a speed of 2.4 GHz and 2 GB of memory. The parameters of HGA after the preliminary tests were set as follows. The population size was equal to 34; the maximum number of iterations was set to be 6000; the converged criterion is achieved when the best solution keeps unchanged for 500 times; the cloning parameter was set at 100%; the crossover rate was set at 100%; the mutation rate was set at 5%; the penalty values were set at the value of total replenishment minus the total supply once constraint (7) is violated. Each test case was executed ten times and the best solution was reported.

Table 2
Parameters of η_{ij}.

i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}	i,j	η_{ij}
1, 2	12.8	1, 3	39.5	1, 10	41.6	1, 20	41.7	1, 30	41.0	1, 40	40.9	1, 50	38.6	1, 60	42.3
1, 70	36.3	1, 80	48.4	2, 3	18.4	2, 4	23.7	3, 4	8.1	4, 5	25.6	6, 7	9.5	6, 8	30.3
7, 9	38.7	8, 9	31.4	8, 10	37.2	9, 10	15.4	9, 11	9.5	11, 12	33.9	11, 13	23.2	11, 20	40.4
11, 30	35.2	11, 40	49.3	11, 50	47.8	11, 70	41.2	11, 80	35.2	12, 13	34.2	12, 14	42.8	13, 14	19.2
13, 15	42.3	14, 16	27.2	15, 17	30.1	16, 17	30.3	16, 18	36.6	17, 18	40.8	17, 19	41.7	18, 19	11.3
19, 20	39.8	19, 21	21.5	20, 22	34.1	21, 23	38.4	21, 30	49.0	21, 40	35.3	21, 50	44.7	21, 60	47.5
21, 80	41.6	22, 23	30.7	23, 24	7.1	23, 25	40.1	24, 25	39.8	24, 26	30.3	25, 26	21.2	27, 29	37.2
28, 29	24.4	28, 30	37.3	29, 31	41.0	30, 31	18.8	30, 32	21.0	31, 33	11.7	31, 40	45.1	31, 50	40.4
31, 60	39.1	31, 70	49.9	31, 80	39.4	32, 33	12.0	32, 34	37.7	33, 34	37.9	33, 35	11.6	34, 35	12.9
35, 37	41.3	36, 37	5.6	37, 38	40.1	38, 39	15.3	38, 40	44.5	39, 40	6.5	39, 41	30.9	40, 41	29.4
40, 42	33.5	41, 42	41.5	41, 43	37.7	41, 50	39.9	41, 60	47.9	41, 70	47.9	41, 80	43.9	42, 43	17.7
42, 44	11.7	43, 44	44.0	43, 45	9.3	44, 46	39.0	45, 46	39.9	45, 47	10.2	46, 48	20.8	47, 49	6.8
48, 50	11.4	51, 52	22.1	51, 60	41.5	51, 70	43.8	51, 80	38.6	52, 53	25.3	52, 54	19.5	53, 55	34.7
54, 55	8.6	54, 56	26.0	56, 58	22.1	57, 58	6.7	57, 59	5.6	58, 59	14.3	58, 60	26.5	59, 60	41.3
59, 61	5.5	60, 62	44.7	61, 63	6.3	61, 80	40.8	62, 63	37.4	62, 64	18.1	64, 65	35.1	65, 66	35.4
65, 67	7.0	66, 67	35.4	66, 68	30.1	67, 69	9.1	68, 70	7.2	69, 71	18.8	70, 71	33.9	71, 72	16.7
71, 73	11.4	72, 73	5.5	73, 74	22.4	73, 75	29.6	74, 75	8.6	74, 76	5.6	75, 76	27.5	76, 77	20.1
76, 78	41.1	77, 78	11.5	77, 79	6.6	78, 79	33.3	79, 80	23.6						

Table 3
Parameters of P_i.

i	p_i	i	p_i	i	p_i	i	p_i	i	p_i	i	p_i	i	p_i	i	p_i
1	519,000	11	632,000	21	214,000	31	87,600	41	521,000	51	592,000	61	598,000	71	22,100
2	96,300	12	572,000	22	8700	32	810,000	42	63,100	52	39,100	62	750,000	72	512,000
3	85,200	13	209,200	23	19,600	33	248,800	43	547,000	53	16,100	63	508,000	73	180,800
4	583,000	14	44,200	24	634,000	34	666,000	44	21,500	54	872,000	64	885,000	74	13,100
5	33,900	15	10,900	25	192,400	35	172,400	45	90,000	55	154,400	65	513,000	75	226,000
6	12,300	16	502,000	26	506,000	36	651,000	46	139,600	56	19,500	66	153,600	76	242,800
7	531,000	17	228,400	27	21,100	37	20,700	47	15,700	57	828,000	67	85,800	77	11,500
8	671,000	18	249,200	28	46,900	38	226,800	48	89,800	58	182,000	68	95,300	78	10,500
9	122,800	19	200,000	29	184,800	39	886,000	49	14,000	59	27,100	69	981,000	79	18,700
10	24,800	20	158,000	30	6400	40	298,800	50	11,400	60	634,000	70	61,700	80	590,000

Table 4
A feasible O–D trip.

n	Nodes passed								
	1	2	3	4	5	6	7	8	9
$h_{ij}(n)$	1	10	9	11	13	11	9	10	1
$B_{1,13}(n)$	20.00	9.60	5.75	17.625	11.825	6.025	3.65	16.15	5.75
$R_{1,13}(n)$	0.0	0.0	14.25	0.0	0.0	0.0	16.35	0.0	14.25
$s_{1,13}(n)$	41.6	15.4	9.5	23.2	23.2	9.5	15.4	41.6	–
$W_{1,13}(n)$	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Using the formula of $\sum_{j=1,j\neq i}^{N}\sum_{m=1}^{M} f_{ij}^{m} = \alpha p_i$, we obtain that the total number of potential users for problem types 1–6 are 1,036,795, 1,371,104, 1,371,104, 2,846,004, 5,695,760 and 5,677,739. Tables 4 and 5 show some refueling information of case 5 of problem type 1. Table 6 shows the Lingo's computational results for problem types 1 and 2. Tables 7–12 show the computational results of GA, CPLEX and HGA for problem types 1–6, respectively. The symbol CP (%) in these Tables denotes the coverage percent, which is the value of dividing the population covered by the total potential users.

Table 5
An infeasible O–D trip.

n	Nodes passed								
	1	2	3	4	5	6	7	8	9
$h_{ij}(n)$	1	10	9	11	12	11	9	10	1
$B_{1,12}(n)$	20.0	9.6	5.75	17.625	9.15	0.675	0.0	16.15	5.75
$R_{1,12}(n)$	0.0	0.0	14.25	0.0	0.0	0.0	20.0	0.0	0.0
$s_{1,12}(n)$	41.6	15.4	9.5	33.9	33.9	9.5	15.4	41.6	–
$W_{1,12}(n)$	0.0	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.0

Table 6
Lingo resluts for problem sizes 1 and 2.

No	ρ	Problem type 1			Problem type 2		
		Sol	Time	CP (%)	Sol	Time	CP (%)
1	1	239,605	7	23.11	212,711	15	15.51
2	2	584,502	54	56.38	454,186	160	33.13
3	3	694,316	281	66.97	620,080	1034	45.22
4	4	794,927	1233	76.67	767,607	5799	55.98
5	5	870,434	1763	83.95	902,481	12,199	65.82
6	6	939,538	12,114	90.62	1,003,160	14,400	73.16
7	7	1,015,045	12,600	97.90	1,124,606	14,400	82.02
8	8	1,036,232	487	99.95	1,194,482	14,400	87.12
9	9	1,036,795	282	100.00	951,797	14,400	69.42
10	10	1,036,795	429	100.00	959,113	14,400	69.95
		Average	2925			9121	

4.2. Illustrative examples

In this subsection, we will use case 5 in Example type 1 to introduce a feasible O–D trip and an infeasible O–D trip. Table 4 shows that the traveling sequence for O–D trip $(1,13)$ starts from node-1, along nodes 10, 9 and 11, to node-13 and then returns from 13, along nodes 11, 9 and 10, back to node-1. The inter-city distances along the path are 41.6, 15.4, 9.5, 23.2, 23.2, 9.5, 15.4 and 41.6. A type-1 AFV with fuel 20 units can travel from node-1 to node-9 on its outbound trip, without recharging. At node-9, the remaining fuel is $B_{1,13}^{1}(3) = 5.75$, which can be used to drive 23Km. The remaining fuel is insufficient to travel the remainder of the trip from node-9 to node-13. Thus, it refuels in the amount of $R_{1,13}^{1}(3) = 14.25$ units at node-9. After that, the vehicle travels to its destination node, 13, where the remaining fuel is $B_{1,13}^{1}(5) = 11.825$ units, and then makes its inbound trip, from node-13 back to the original node. At node-9 of the return trip, the remaining fuel is $B_{1,13}^{1}(7) = 3.65$ units and the vehicle refuels in the amount of $R_{1,13}^{1}(7) = 16.35$ units at node-13 and then returns to its original node, 1, without further recharging. Thus, the O–D trip $(1,13)$ is a feasible O–D trip.

Table 5 shows that the traveling sequence for the O–D trip $(1,12)$ starts from node-1, along nodes 10, 9 and 11, to node-12 and then returns from 12 along nodes 11, 9 and 10, back to node-1. On this trip, the AFV can only recharge at location 9. The inter-city distances along the path are 41.6, 15.4, 9.5, 33.9, 33.9, 9.5, 15.4 and 41.6. A type-1 AFV with fuel $B_{1,12}^{1}(1) = 20.0$ units can travel from node-1 to node-9 on its outbound trip, without recharging. At node-9, the remaining fuel is $B_{1,12}^{1}(3) = 5.75$ units. The remaining fuel is insufficient to complete the trip from node-13 to node-10. Thus, it recharges in the amount of $R_{1,12}^{1}(3) = 14.25$ units at node-9. After that, the vehicle travels to its destination node-12, where the remaining fuel is 9.15, and then

Table 7
Computational resluts for problem size 1.

No	ρ	GA			CPLEX			HGA			Gap		
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HL (%)	HG (%)	HC (%)
1	1	239,605	3	23.11	237,828	2	22.94	239,605	2	23.11	0.00	0.00	0.75
2	2	584,502	7	56.38	584,502	524	56.38	584,502	1	56.38	0.00	0.00	0.00
3	3	694,316	5	66.97	694,066	846	66.94	694,316	2	66.97	0.00	0.00	0.04
4	4	794,927	7	76.67	792,564	1103	76.44	794,927	2	76.67	0.00	0.00	0.30
5	5	870,434	10	83.95	870,184	543	83.93	870,434	4	83.95	0.00	0.00	0.03
6	6	939,538	11	90.62	930,631	534	89.76	939,538	6	90.62	0.00	0.00	0.96
7	7	1,015,045	11	97.90	978,534	534	94.38	1,015,045	5	97.90	0.00	0.00	3.73
8	8	1,036,232	11	99.95	1,031,242	3	99.46	1,036,232	5	99.95	0.00	0.00	0.48
9	9	1,036,759	11	100.00	1,036,795	2	100.00	1,036,795	4	100.00	0.00	0.00	0.00
10	10	1,036,759	9	100.00	1,036,795	2	100.00	1,036,795	4	100.00	0.00	0.01	0.00
		Average	8.5			356			3.4		0.00	0.00	0.63

Budget H = 1,125,000ρ.

Table 8
Computational results for problem size 2.

No	ρ	GA			CPLEX			HGA			Gap		
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HL (%)	HG (%)	HC (%)
1	1	212,711	5	15.51	212,711	544	15.51	212,711	1.7	15.51	0.00	0.00	0.00
2	2	454,186	12	33.13	454,186	14,400	33.13	454,186	1.4	33.13	0.00	0.00	0.00
3	3	620,080	18	45.22	620,080	14,400	45.22	620,080	2.9	45.22	0.00	0.00	0.00
4	4	767,607	25	55.98	767,607	10,803	55.98	767,607	4.4	55.98	0.00	0.00	0.00
5	5	902,481	21	65.82	902,481	10,801	65.82	902,481	4.3	65.82	0.00	0.00	0.00
6	6	1,023,927	27	74.68	1,023,927	10,802	74.68	1,023,927	5.7	74.68	2.07	0.00	0.00
7	7	1,124,436	25	82.02	1,124,606	10,803	82.02	1,124,606	5.3	82.02	0.00	0.02	0.00
8	8	1,194,482	33	87.12	1,187,959	1926	86.64	1,194,482	6.3	87.12	0.00	0.00	0.55
9	9	1,253,086	28	91.94	1,221,602	632	89.10	1,260,430	8.7	91.93	32.43	0.59	3.18
10	10	1,297,864	32	94.66	1,270,575	123	92.67	1,297,864	10.9	94.66	35.32	0.00	2.15
		Average	23.6			7524			5.2		6.98	0.06	0.59

Table 9
Computational resluts for problem size 3.

No	ρ	GA			CPLEX			HGA			Gap	
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HG (%)	HC (%)
1	1	212,711	8	15.51	212,711	524	15.51	212,711	2.7	15.51	0.00	0.00
2	2	454,186	11	33.13	454,186	7140	33.13	454,186	1.5	33.13	0.00	0.00
3	3	620,080	12	45.22	620,080	14,401	45.22	620,080	2.7	45.22	0.00	0.00
4	4	767,607	13	55.98	767,607	14,404	55.98	767,607	3.2	55.98	0.00	0.00
5	5	902,481	15	65.82	902,481	14,403	65.82	902,481	3.9	65.82	0.00	0.00
6	6	1,023,927	20	74.68	1,023,967	14,403	74.68	1,023,927	5.3	74.68	0.00	0.00
7	7	1,124,606	23	82.02	1,124,606	14,403	82.02	1,124,606	6.2	82.02	0.00	0.00
8	8	1,194,482	23	87.12	1,185,136	5268	86.44	1,194,482	4.8	87.12	0.00	0.79
9	9	1,242,559	26	91.62	1,245,475	473	90.84	1,260,430	5.4	91.93	1.44	1.20
10	10	1,260,600	28	91.94	1,255,252	8660	91.55	1,294,027	6.2	94.38	2.65	3.09
		Average	17.9			9408			4.2		0.41	0.51

Table 10
Computational resluts for problem size 4.

No	ρ	GA			CPLEX			HGA			Gap	
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HG (%)	HC (%)
1	11	2,070,002	165	72.73	1,674,326	14,400	58.83	2,070,002	59.6	72.73	0.00	23.63
2	12	2,221,103	748	78.04	1,724,617	14,400	60.60	2,221,103	67.7	78.04	0.00	28.79
3	13	2,319,140	820	81.49	2,316,062	14,400	81.38	2,319,140	193.7	81.49	0.00	0.13
4	14	2,419,315	805	85.01	2,349,875	14,400	82.57	2,440,573	163.7	85.75	0.88	3.86
5	15	2,485,528	885	87.33	2,419,560	14,400	85.02	2,510,107	190.5	88.20	0.99	3.74
6	16	2,538,853	376	89.21	2,545,342	14,400	89.44	2,616,114	168.1	91.92	3.04	2.78
7	17	2,572,941	234	90.41	2,553,224	14,400	89.71	2,667,831	149.7	93.74	3.69	4.49
8	18	2,686,580	229	94.40	2,695,935	607	94.73	2,782,213	212.0	97.76	3.56	3.20
9	19	2,729,566	228	95.91	2,648,944	1036	93.08	2,806,471	195.7	98.61	2.82	5.95
10	20	2,732,207	229	96.00	2,609,886	135	91.70	2,807,559	188.5	98.65	2.76	7.57
		Average	471.9			10,258			158.9		1.77	8.41

Table 11
Computational results for problem size 5.

No	ρ	GA			CPLEX			HGA			Gap	
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HG (%)	HC (%)
1	25	5,540,413	2875	97.27	4,275,710	14,427	75.07	5,604,381	1622.8	98.40	1.15	31.07
2	26	5,571,532	3384	97.82	4,942,423	14,425	86.77	5,653,848	1405.8	99.26	1.48	14.39
3	27	5,602,752	3352	98.37	5,313,460	5395	93.29	5,678,514	1635.8	99.70	1.35	6.87
4	28	5,618,306	3574	98.64	5,438,412	3059	95.48	5,685,562	1228.0	99.82	1.20	4.54
5	29	5,624,998	3174	98.76	5,543,976	3300	97.34	5,687,648	1604.6	99.86	1.11	2.59
6	30	5,635,458	3612	98.94	5,330,962	4646	93.60	5,693,048	1501.3	99.95	1.02	6.79
7	31	5,640,882	3780	99.04	5,420,914	2388	95.17	5,695,332	1479.5	99.99	0.97	5.06
8	32	5,643,432	3444	99.08	5,411,392	2117	95.01	5,695,747	1933.6	100.00	0.93	5.25
9	33	5,654,192	4541	99.27	5,503,381	2509	96.62	5,695,760	1111.8	100.00	0.74	3.50
10	34	5,661,364	3612	99.40	5,366,527	1665	94.22	5,695,760	1188.9	100.00	0.61	6.13
			3535			5393			1471		1.06	8.62

Table 12
Computational results for problem size 6.

No	ρ	GA			CPLEX			HGA			Gap	
		Sol	Time	CP (%)	Sol	Time	CP (%)	Sol	Time	CP (%)	HP (%)	HG (%)
1	26	4,825,387	4432	84.99	4,044,087	14,400	71.23	4,993,529	1445	87.95	3.48	23.48
2	27	5,045,510	3846	88.86	4,345,298	14,400	76.53	5,095,280	1933	89.74	0.99	17.26
3	28	5,075,347	3045	89.39	4,468,954	14,400	78.70	5,167,769	1326	91.02	1.82	15.65
4	29	5,172,304	3979	91.10	4,578,486	14,400	80.64	5,259,438	1486	92.63	1.68	14.87
5	30	5,179,767	4494	91.23	4,811,435	14,400	84.74	5,325,889	1605	93.80	2.82	10.69
6	31	5,354,149	2796	94.30	4,954,600	14,400	87.26	5,364,137	1356	94.48	0.19	8.27
7	32	5,429,007	4737	95.62	4,985,308	14,400	87.80	5,439,673	2054	95.81	0.20	9.11
8	33	5,487,029	3985	96.64	5,053,245	14,400	89.00	5,543,972	1301	97.64	1.04	9.71
9	34	5,497,476	4002	96.83	5,060,361	14,400	89.13	5,570,938	2269	98.12	1.34	10.09
10	35	5,499,175	4803	96.86	5,074,493	14,400	89.38	5,573,087	1719	98.16	1.34	9.83
			4009			14,400			1649		1.49	12.90

makes its inbound trip from node-12 back to the original node. At node-11 of the return trip, the fuel remaining is $B^1_{1,12}(6) = 0.675$ units, which can only be used to drive 27Km and is not sufficient to go from node-11 to node-9 to recharge. Thus, the O–D trip $(1, 12)$ is not a feasible O–D trip.

4.3. Computational results and disscussions

The values of *CP* in Tables 6–12 show that the population coverage ratio does not decrease with the increase of budget. These values can be used to determine the budget to reach a given population coverage ratio. For example, if the required population coverage ratio is 80%, column eleven of Table 7 shows that it is enough to budget 5 × \$1,125,000 = \$5,625,000 ($\rho = 5$) to build recharging stations. In addition, from the change in the population coverage, it is approximately seen that the marginal population coverage falls as the investment budget rises. This fact can help decision makers to determine whether or not to build additional recharging station. That is, the decision to increase the budget depends on whether or not the marginal benefit from the change in population coverage exceeds the budget increase.

From column eleven of Table 7, we observe that not all potential users are covered for problem instances 1–8 (ρ is from 1 to 8). For example, the demand covered in problem instance 5 is 870,434. In this case, the recharging stations are set at locations 1, 4, 9, 14 and 15. From the recharging capacity and fuel consumption coefficient, it is known that the driving range of AFV type-1 is 100 (km). The computational results show that a type-1 AFV can complete 173 out of 220 O–D trips using these established recharging stations. Therefore, there are 173 feasible O–D itineraries and 37 infeasible O–D itineraries. For shortening the paragraph, we only illustrate why O–D trips $(1, 13)$ is a feasible O–D itinerary and $(1, 12)$ is an infeasible itinerary.

The performance of the proposed heuristic approach is now discussed. To measure the performance of the proposed HGA (hybrid genetic algorithm), the conventional genetic algorithm (GA) and the commercial software GAMS/CPLEX modeling language were also used to solve for all test problems. In addition, the solutions using Lingo global solver were confirmed to be global for problem type 1. However, Lingo global solver failed to produce global solutions for problem types 2–4 after 4 h of computational time, due to the complexity of the problem structure. Moreover, the solutions obtained by Lingo were worse to those of GAMS/CPLEX for problem types 3–6. Thus, in this paper we only report Lingo solutions for problem types 1 and 2.

The criteria for the performance of methods were the quality of the population coverage and the amount of CPU time used. In this paper, the gap, defined as 100 (solution obtained by Lingo/GA/CPLEX – best feasible solution obtained by *HGA*)/solution obtained by Lingo/GA/CPLEX, is used to evaluate the solution qualities for all instances and all problem types.

The symbols, HL, HG and HC, represent the solution percentage gaps between the HGA solutions and the Lingo solutions, between the HGA solutions and the GA solutions, and between the HGA solutions and the CPLEX solutions, respectively. In addition, all algorithms were terminated if the execution time exceeded 4 h.

In terms of solution quality, Table 7 shows that HGA and GA obtained the optimal solutions for all test cases of problem type 1 while CPLEX can only obtain optimal solutions in 3 out of 10 cases. Therefore, HGA and GA perform better than CPLEX for small test problems. For problem type 2, Table 8 shows that the feasible solutions found by HGA and GA are the same and they are all better than or equal to the feasible solutions found by CPLEX and Lingo. For problem types 3–6, in terms of solution quality, Tables 9–12 show that the feasible solutions found by HGA are all better than or equal to the feasible solutions found by Lingo, GA and CPLEXL. Thus, in terms of solution quality, we conclude that HGA performs better than GA and CPLEX for all problems. Moreover, we also conclude that for reaching a given population coverage, the required budget of recharging stations by HGA will be lower than that of CPLEX.

In terms of running time, the average computational time required to solve test cases by Lingo, GA, CPLEX and HGA, respectively, are 2925, 8.5, 356 and 3.4 s for problem type-1, 9121, 23.6, 7524 and 5.2 s for problem type-2. The average computational time required to solve test cases by GA, CPLEX and HGA, respectively, are 17.9, 9408 and 4.2 s for problem type-3, 471.9, 10,258 and 158.9 s for problem type-4, 3535, 5393 and 1471 s for problem type-5 and 4009, 14,400 and 1649 s for problem type-6. It implies that the average CPU time used by HGA for finding feasible solutions was much less than the average times required for GA, CPLEX and LINGO Accordingly, from Tables 6–12 show that HGA outperforms CPLEX, GA and LINGO, with respect to solution quality and computational time, for larger problems. In addition, HGA and GA nearly obtain the same solution in all problem types. However, HGA slightly performs well than GA with respect to computational time.

5. Conclusion

This paper deals with the problem of the location of recharging stations for alternative-fuel vehicles with multiple station types. The purpose is to determine the locations and types of recharging stations under budget restrictions, in order to maximize the population coverage.

In this wok, people for a trip are counted as members of the covered population once their round-trip can be completed. An AFV can complete a trip if it has enough energy or it can be recharged on the way to complete the journey. Thus, for a long O–D trip, one or more stations must be located on the path within vehicle's driving range, so that the O–D trip can be completed. However, when there is a limited budget, there is competition for resources in a network with multiple O–D trips. This problem belongs to the class of NP-complete combinatorial optimization problems. This paper has developed an efficient hybrid genetic algorithm to obtain a compromised solution within a reasonable CPU time. The computational results are summarized as follows.

1. The budget has a direct impact on the number of recharging stations.
2. The marginal population coverage decreases when the investment budget increases. Therefore, if a model with a base budget is defined as a basic model and a model with a base budget and an additional investment is defined as an extension model, the results derived from these models will be useful for decision makers to make a cost-benefit analysis.
3. In terms of solution quality and computational efficiency, the HGA's feasible solutions are better than those of conventional genetic algorithm and GAMX/CPLEX for all test problems (Problem types 1–6). Thus, for reaching a given population coverage, the budget of recharging stations needed by HGA will be lower than that by CPLEX.

Acknowledgments

The authors would like to thank anonymous referees for their helpful comments and suggestions that greatly improved the presentation of this paper. This research is partially supported by National Science Council, Taiwan, under Grant NSC 101-2221-E-415-006-MY2.

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