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An optimal charging location model of an automated electric taxi system considering two types of charging

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Abstract — **In this paper, we propose an optimization model to select the charging locations of an automated electric taxi (AET) system. The service provided by this AET system is a seamless door-to-door service connected to the train station, which helps improve the last mile transport. We individualize the vehicles instead of treating them as a flow to track the remaining battery level of each AET. Two types of charging are considered containing depot charging with lower charging speed and opportunity charging with higher charging speed. We formulate a mixed-integer programming model with linear constraints to optimize the locations of depot charging and opportunity charging according to the objective function of maximizing the number of satisfied requests. The proposed model is applied to the case study city of Delft, the Netherlands with the travel demand generated by the Delft Zuid train station. Results show that the charging scheme with two types of charging can provide sufficient electrical energy for shared use AETs to serve passengers' last mile travel demand.**

I. Introduction

Electric vehicles (EVs) are supposed to benefit the environment due to the low-carbon electricity as well as the high energy efficiency of electric motors [1], [2]. Regarding an urgent need to improve the sustainability of the transport system, a transition is required from fossil fuel dependent-vehicles towards alternative transports such as electric mobility (e-mobility). In recent years, many R&D and pilot studies have been conducted to identify the motivators and barriers of EV uptake and usage around the world. These include exploring the factors on EV market diffusion [1], the effectiveness of EV incentives [2], demand for charging infrastructure [3], [4], etc. The results of these research projects provide significant directions for the decision-makers in producing EV incentives.

Apart from introducing EVs into the transport system, driving automation is also expected to bring significant benefits such as higher safety, lower traffic congestion, lower transport costs, lower usage of parking space, etc [5]. Automated vehicles (AVs) could reduce labour costs and relieve travellers from driving to other activities like leisure or work. A possible area of application for AVs is public transport [6]. The concept of automated taxis (ATs) is supposed to offer a seamless door-to-door service within a city area for all passengers. With the advent of automation, using ATs in urban transport systems creates a new type of shared transport system. On the one hand, they are similar to traditional taxis regarding their flexibility, but on the other hand, they bring benefits in terms of costs and safety [7].

EVs need to be recharged at charging stations more frequently than combustion vehicles. The need for charging, which could lead to operation idleness, is generally regarded as one of the most significant barriers for these vehicles to be used in public transport. The EU has announced the target of one charging point per 10 EVs to guarantee the level of usage. It aims to enable users to charge their vehicles within Europe without any barriers [8]. At the same time, AVs make the relocation of a shared-use vehicle system easy and economical. Therefore, we may expect to use automated electric taxis (AETs) in the urban area for the last mile connection soon. However, research on optimizing the charging scheduling and the distribution of charging infrastructure is limited and studies are needed to provide optimal solutions to such an AET system.

In this paper, we use AVs as taxis with fully electric power as a feeder service to train stations to make this public transport mode more environment-friendly and sustainable. The proposed AET system will provide the last mile service to/from the train station in a seamless way considering the possibility of the vehicles to travel without any drivers as a relocation method. The AET system is supposed to contribute to the attractiveness and sustainability of public transport.

Most of the literature on analysing the charging location is to optimize the public charging stations for private EV users [9]–[11]. Li and Shirk introduced an optimal charging decision-making framework for private used AEVs [10]. This framework provides the choice of charging station and the amount of charged energy using the data of existing charging infrastructure and predicted personal energy consumption. However, Shahraki. et al focused on the charging problem by considering the real-

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world vehicle travel patterns combined with private EVs and public EVs [11]. They proposed an optimization model to select locations of public charging stations to maximize the total travel distance using electric power. Based on the case study in Beijing, China with 11880 vehicles' trajectory data, they concluded that the 40 optimal charging locations can increase electrified travel distance by 59% and 88% for slow and fast charging respectively.

A few studies have focused on the optimization charging problem of shared use EVs but mainly considered single type charging, i.e. charging by one kind of charging infrastructure [12][13]. Iacobucci et al. proposed a combined model: a. optimizing the charging with vehicle-to-grid; b. optimizing the vehicles' routing and relocation [13]. However, they only used single type charging: either a higher charging speed or a lower charging speed instead of a combined two-type charging.

Therefore, it is essential to find the optimal solution for the charging problem of shared use EVs with different charging infrastructure. In this paper, we propose a mathematical model to optimize the charging scheduling problem of an AET system with two types of charging: depot charging and opportunity charging, considering the travel demand of connecting train trips.

This paper is organized as follows: firstly we present the mathematical model to solve the optimal location problem of an AET system with two types charging in section II. Then we apply this model to the case-study city of Delft, the Netherlands, and the results are shown in section III. The paper ends with conclusions in section IV.

II. MATHEMATICAL MODEL

This section describes a linear mix-integer programming model to determine the optimal locations of the opportunity and depot charging in the two-type charging system.

We consider the last mile transport service provided by AETs for train passengers. The AET company can achieve total control of the system, meaning that each vehicle's travel task and charging task are assigned by the company's control centre. The urban area of the target city is divided into several zones and the travel demand is generated between the train station and these zones with the desired departure time. Since this is the last mile service, the travel demand between service zones (without train stations) is not considered. We treat the origins or destinations of passengers' travel demand in the same zone as the centroid of that zone for simplification purposes. The travel requests are assumed to be known before the optimization by pre-booking. In order to track the remaining battery energy of each vehicle, the model individualizes the AETs and the travel requests instead of treating them as flows.

The charging issue of the AET system is considered in two levels: depot charging and opportunity charging. The depot charging is to charge the vehicle batteries during the longer operation pauses (e.g. after the service open time of an AET system) exclusively at the depot with slow charging speed (lower than 10kW). The opportunity charging is to charge the AETs several times during their operation hours, primarily during dwell times with fast charging speed (11-23kW). It is advised to do a 100% charge for the sake of batteries' life. Therefore, we assume that all the AETs start in the depot at the beginning of the operation time and also go back to the depot at the end of the operation time. When they start, the vehicle batteries are already fully charged by depot charging in the operation pause. Then the AETs will only charge their batteries at the opportunity charging location with a faster charging speed but shorter charging time. We will set a maximum charging time for the opportunity charging to let the AETs charge shortly but frequently at the opportunity charging station so that the operation will not be severely disturbed by charging. The description of the charging scheme with two types of charging is shown in TABLE 1.

TABLE 1 CHARGING SCHEME WITH TWO TYPES OF CHARGING

	Depot charging	Opportunity charging
Charging range	100%	up to 80%
Charging speed	Slow	Fast
Location	Suburban area	Urban area
Charging time	Out of operation time	Within operation time

We focus on the charging scheduling of the AET system so the routing of the vehicles is simplified as the route choice and the impact of traffic congestion on travel time are not considered. As a result, the travel time between every OD pair is constant and is an input for this optimization problem. Parking is allowed in all the zones since we assume that the AETs can use the public parking space for their dwell time. However, opportunity charging activities are also considered as parking in the zones which are selected as the opportunity charging location. This model does not allow ride-sharing for several clients to be pooled together, meaning that the system accepts only individual trips for each passenger.

A set of depot charging and a set of opportunity charging zone candidates are considered where the AETs can conduct their charging activities. We establish an optimization model with mixed-integer variables to decide the optimal locations of depot charging and opportunity charging for such an AET system with travel requests generated in a typical day. In this model, the maximum number of depot charging locations and opportunity charging locations are set as parameters. And the AET company is free to accept or reject requests

since some of the travel demand may be rejected due to the limited resources i.e. vehicles and energy.

The notation used in this model is presented as follows:

Sets

$\boldsymbol{I}$	$= \{1, \dots, i, \dots I\}$, set of zones in the network, where I is the total number of zones.
$\boldsymbol{I_o}$	set of candidate zones where an opportunity charging station may locate, $\boldsymbol{I_o} \subset \boldsymbol{I}$
$\boldsymbol{I_d}$	set of zones where depot charging is located, $\boldsymbol{I_d} \subset \boldsymbol{I}$
$\boldsymbol{T}$	$= \{0, \dots, t, \dots, T\}$ set of time instants in the optimization period, where T is the total number of time steps in the operation time. We use time instants to describe the instantaneous state of the AET system, where between two sequential time instants is one time step.
$\boldsymbol{V}$	$= \{1, \dots, v, \dots, V\}$, set of vehicles, where V is the total number of taxis in the system.
$\boldsymbol{M}$	$=\{\dots, (i, j, t), \dots\}$, set of travel requests from origin i to j from time instant t

Parameters

$q_{i,j,t}$	set of travel requests from origin i to j from time instant t
cap_i	maximum capacity for candidate i
r	battery range in distance
r_0	battery charging speed in travel distance
δ_{ij}	travel time
d_{ij}	travel distance
θ	the lowest percentage of battery range allowing to travel
σ	the highest percentage of battery range the opportunity charging can reach
a	maximum number of opportunity charging stations
b	maximum number of depot charging stations

Decision variables

$S_{i,j,t}^v$	binary variable equal to 1 if vehicle v drives from i to j from time instant t, otherwise 0, $\forall i, j \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T}, \forall v \in \boldsymbol{V}$
$P_{i,t}^v$	binary variable equal to 1 if vehicle v parking at zone i from t to $t+1$, otherwise 0, $\forall i \in \boldsymbol{I}, \forall t \in \boldsymbol{T}, \forall v \in \boldsymbol{V}, t < \boldsymbol{T}$
$Q_{i,j,t}^v$	binary variable equal to 1 if travel request (i, j, t) is satisfied by vehicle v, otherwise 0, $\forall (i, j, t) \in \boldsymbol{M}, \forall v \in \boldsymbol{V}$
x_i	binary variable equal to 1 if an opportunity charging station is located at zone i, otherwise 0, $\forall i \in \boldsymbol{I_o}$
y_i	binary variable equal to 1 if a depot charging station is located at zone i, otherwise 0, $\forall i \in \boldsymbol{I_d}$
R_t^v	the remaining energy expressed in units of distance at time instant t of vehicle v, $\forall t \in \boldsymbol{T}, \forall v \in \boldsymbol{V}$

The optimization model for solving the problem defined above has the following formulation. The objective function is:

$$max\ Z = \sum_{(i,j,t) \in \boldsymbol{M}, v \in \boldsymbol{V}} Q_{i,j,t}^v \tag{1}$$

Subject to:

$$\sum_{j \in \boldsymbol{I}} S_{j,i,t-\delta_{ij}}^v + P_{i,t-1}^v = \sum_{j \in \boldsymbol{I}} S_{i,j,t}^v + P_{i,t}^v \qquad \forall i \in \boldsymbol{I}, \forall t \in \boldsymbol{T}, \forall v \in \boldsymbol{V}, t > 0, t < T \tag{2}$$

$$\sum_{\substack{i,j \in \boldsymbol{I}, t_1 \in \boldsymbol{T} \\ t_1 \le t, t_1 + \delta_{ij} > t}} S_{i,j,t_1}^v + \sum_{i \in \boldsymbol{I}} P_{i,t}^v = 1 \qquad \forall t \in \boldsymbol{T}, \forall v \in \boldsymbol{V}, t < T \tag{3}$$

$$\sum_{j \in \boldsymbol{I}} S_{i,j,0}^v = y_i \qquad i \in \boldsymbol{I_d}, \forall v \in \boldsymbol{V} \tag{4}$$

$$\sum_{v \in \boldsymbol{V}} Q_{i,j,t}^v \le q_{i,j,t} \qquad \forall (i, j, t) \in \boldsymbol{M} \tag{5}$$

$$Q_{i,j,t}^v \le S_{i,j,t}^v \qquad \forall (i, j, t) \in \boldsymbol{M}, \forall v \in \boldsymbol{V} \tag{6}$$

$$R_t^v = r - \sum_{\substack{i,j \in \boldsymbol{I}, t_1 \in \boldsymbol{T} \\ t_1 + \delta_{ij} \le t}} S_{i,j,t_1}^v \cdot d_{ij} + \sum_{\substack{i \in \boldsymbol{I_o}, t_2 \in \boldsymbol{T} \\ t_2 + 1 \le t}} P_{i,t_2}^v \cdot r_0 \qquad \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{7}$$

$$R_t^v \ge \theta \cdot r \qquad \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{8}$$

$$R_t^v \le \sigma \cdot r \qquad \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{9}$$

$$\sum_{v \in \boldsymbol{V}} P_{i,t}^v \le x_i \cdot cap_i \qquad \forall \boldsymbol{i} \in \boldsymbol{I_o}, \forall \boldsymbol{t} \in \boldsymbol{T}, \boldsymbol{t} < \boldsymbol{T} \tag{10}$$

$$\sum_{\substack{t \in \boldsymbol{T}, v \in \boldsymbol{V} \\ t < T}} P_{i,t}^v \ge x_i \qquad \forall \boldsymbol{i} \in \boldsymbol{I_o} \tag{11}$$

$$\boldsymbol{P_{i,t}^v + P_{i,t+1}^v + P_{i,t+2}^v \le 2} \qquad \forall \boldsymbol{i} \in \boldsymbol{I_o}, \forall \boldsymbol{t} \in \boldsymbol{T}, \boldsymbol{t} < \boldsymbol{T} - \boldsymbol{2} \tag{12}$$

$$\sum_{i \in \boldsymbol{I_o}} x_i \le a \tag{13}$$

$$\sum_{i \in \boldsymbol{I_d}} y_i \le b \tag{14}$$

$$S_{i,j,t}^v \in \{0,1\} \qquad \forall \boldsymbol{i}, \boldsymbol{j} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{15}$$

$$P_{i,t}^v \in \{0,1\} \qquad \forall \boldsymbol{i} \in \boldsymbol{I}, \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V}, \boldsymbol{t} < \boldsymbol{T} \tag{16}$$

$$Q_{i,j,t}^v \in \{0,1\} \qquad \forall (\boldsymbol{i}, \boldsymbol{j}, \boldsymbol{t}) \in \boldsymbol{M}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{17}$$

$$x_i \in \{0,1\} \qquad \forall \boldsymbol{i} \in \boldsymbol{I_o} \tag{18}$$

$$R_t^v \ge 0 \qquad \forall \boldsymbol{t} \in \boldsymbol{T}, \forall \boldsymbol{v} \in \boldsymbol{V} \tag{19}$$

Our objective (1) is to maximize the number of satisfied requests when the number of AETs and obtaining energy from charging are both limited.

Constraints (2) are the flow conservation constraints which make sure that the number of AETs leaving from zone i and parking there from time instant t is equal to the number of AETs arriving at zone i and parking at the same place until t. The variable $S_{i,j,t}^{v}$ includes the AET's relocation without any drivers. This indeed takes the advantage of AVs to diminish the negative impact of taxi imbalance in a taxi system. Constraints (3) guarantee that each vehicle v can only have one status at time instant t: either on the way to the next zone or parking at some zone. Constraints (4) assure that vehicle v can only drive from zone i from the beginning of the operation time when zone i is selected as a depot charging location. Constraints (5) impose that a travel request $q_{i,j,t}$ can only be served by one vehicle or be rejected. In this model we do not consider waiting time, which means the travel request $q_{i,j,t}$ can only be served at time t without any delay or be rejected. Constraints (6) assure that a travel request can only be served by vehicle v when AET v is travelling between the origin and destination of this travel request. Constraints (7) compute the remaining energy of vehicle v at time instant t in travel distance which equals to the full battery range from the depot minus the total travel distance until t plus the energy obtained when this vehicle charges at the opportunity charging locations. Constraints (8) assure that the remaining energy of the vehicle's battery in travel distance at any time cannot be lower than the lowest energy percentage θ. This is to make sure that the AETs will not drive with low battery. Constraints (9) assure that the remaining energy of the vehicle's battery at any time cannot exceed the highest battery percentage σ. This is due to the feature of battery: when the battery reaches about 80% of the state of charge (SOC), the opportunity charging becomes slow and less necessary. So in this model, we set this maximum battery percentage to guarantee that AETs can efficiently obtain enough energy. Constraints (10) limit the number of charging vehicles in an opportunity charging zone to its capacity. Besides, if a zone is not selected as an opportunity charging zone, then no vehicle can charge there. Constraints (11) guarantee that if no AET will be charged in zone i, then this zone will not be selected as an opportunity charging zone. Constraints (12) impose that a vehicle can charge at an opportunity charging station at most two time steps. Constraints (13) and (14) limit the maximum number of charging zones for opportunity charging and depot charging. Constraints (15)-(19) define the domain of the decision variables.

III. CASE STUDY AND RESULTS

We apply our model to the case-study city of Delft, the Netherlands. This city has a total area of 24 km^2 and a population of about 101,400. Delft has two train stations while we concentrate on Delft Zuid station which is located in the south of Delft. We divided the catchment area of Delft Zuid station into 32 service zones following the principle of homogeneous land use in each zone. The average size of each zone is about 0.5 km ×0.5 km. The demand zones of the Delft case study are shown in FIGURE 1. Considering the low cost of land use, we choose 3 zones in the outskirt of the city as the candidates for depot charging. Also, 8 zones out of 32 zones in different areas of the city are selected as the candidates for opportunity charging locations.

We choose 6:00-22:00 as the service time of AET company to provide transport service for the connected train trips. The time step is set as 5 min meaning that there will be 192 time steps for the 16 hours' operation time. The travel distance and travel time between service zones are calculated by the open map service Google Maps.

FIGURE 1 DEMAND ZONES OF DELFT CASE STUDY

The mobility data is obtained from a face to face field survey at Delft Zuid train station in 2015 [14]. The survey is a stated preference of the passengers for using the AETs and the probabilities of service zones to be the origin or destination in this connected train trips. The average headway of the trains stop at Delft Zuid station is 15 min for both directions. We assume that the passengers arrive at the train station before the train departure time according to a uniform distribution. Correspondingly, the passengers who get off the train are assumed to leave the train station and go to their destinations immediately. We use the Monte Carlo simulation to generate the travel requests for AETs based on the estimated probabilities described above. The total number of travel requests for AET is 100 with 50% arriving at the train station and 50% leaving the station. They are mainly concentrated in two peak periods: 7:00-9:00 am and 4:00-6:00 pm.

We choose Renault Twizy as our vehicle and use its technical parameters as the charging parameters of AET in this model. The battery range of this vehicle is 80 km. In order to simplify the relationship between the charging speed, battery level and travel distance, we assume that the charging of the vehicle battery is uniform meaning that with every time step the battery will obtain the same amount of travel distance regardless of the battery level.

We test the proposed model in several scenarios with different inputs and compare the results to analyse the performance of such an AET system. The model is programmed in the Mosel language and solved with the FICO® Xpress solver version 8.5 in a Xeon processor @3.60GHz, 32 GB RAM computer under a Window 1-64-bite operation system.

A Variation in the fleet size

Three scenarios are built with a fleet of 1, 5 and 10 AETs for the proposed model when the maximum number of the opportunity charging station is 4 and the maximum number of the depot charging station is 1. The results obtained from the optimization model are presented in TABLE 2 and FIGURE 2.

TABLE 2 OPTIMIZATION RESULTS FOR THE VARIATION IN THE FLEET SIZE

Fleet size	**Obj.**	**No. of OC***	**Total charging time (min)**	**Avg. charging time /AET (min)**	**Avg. satisfied requests /AET**	**Avg. driving distance /AET (km)**
1	22	4	70	70	22	67
5	64	4	100	20	12.8	28.4
10	88	4	115	11.5	8.8	24.8

*OC: opportunity charging

In the scenario of 1 AET, 22 out of 100 requests are satisfied. Even though this scenario has the lowest satisfying rate but it has the highest vehicle usage among these three scenarios: it serves 22 requests, travels 67 km and charges 70 min per AET. When the fleet size increases to 5, the number of satisfied requests has a significant growth: from 22 to 64. Having more AETs not only increases the number of accepted requests but also decreases the demand for opportunity charging. The total charging time of all the AETs at all the opportunity charging stations grows from 70 min to 100 min but the average charging time per AET drops from 70 min to 20 min. This indicates that the more vehicles that are needed, the more battery energy is needed to improve the transport capability of the AET system. When the number of AETs goes to 10, the satisfied requests keep increasing and so as the charging time. However, the vehicle usage is lower than the second scenario and is the lowest among the three scenarios: only 24.8 km driving per AET and 8.8 requests served by each AET. Besides, the percentage of satisfied requests does not reach 100% of these three scenarios. This is because this model assumes that the travel requests cannot be satisfied with any delay. As a result, the AET system guarantees high-quality service (zero delay time) but loses the flexibility to some extent. When the number of AETs is fixed, some of the travel requests cannot be satisfied due to the limited number of vehicles.

(a) Optimal charging locations with 1 AET

(b) Optimal charging locations with 5 AETs

(c) Optimal charging locations with 10 AETs

FIGURE 2 OPTIMAL CHARGING LOCATIONS FOR VARIATION IN THE FLEET SIZE

The optimal locations for the opportunity charging for variation in the fleet size can be seen in FIGURE 2. All of the three scenarios decide to select 4 zones as the location of the charging stations. But the solutions are not the same. First of all, they all select the zone of the train station as one of the locations for charging. This is because all the travel demand is connected with the train station and this zone is the most convenient one to charge the AETs. Secondly, they all select the zone on the west side of the city as one location, but the charging time there is different. When only one AET is available in the system, the western zone is the main charging location with the highest charging time. However, with the increase of fleet size, this charging station becomes less important and the locations on the east and south side turn to be highly used. Considering that the satisfied requests are different due to different fleet sizes, the optimal locations of the opportunity charging also change with the demand pattern.

The location of the depot charging does not change with the fleet size. The zone on the southeast of the city

is always the best location for depot charging where all the fully charged AETs start their trip from there.

B Variation in the number of opportunity charging locations

We select 5 AETs as the fixed fleet size and vary the maximum number of opportunity charging locations with 2, 4, and 6 to conduct a comparison of system performance.

TABLE 3 OPTIMIZATION RESULTS FOR THE VARIATION IN THE NUMBER OF OPPORTUNITY CHARGING LOCATIONS

a	Obj.	No. of OC*	Total charging time (min)	Avg. charging time /AET (min)	Avg. satisfied requests /AET	Avg. driving distance /AET (km)
2	63	2	115	23	12.6	36.6
4	64	4	110	22	12.8	28.4
6	65	5	105	21	13.0	27.4

*OC: opportunity charging

The results are presented in TABLE 3. It can be seen that the value of a (maximum number of opportunity charging location) does not influence the AET system's performance regarding the travel request satisfaction. When at most two charging locations are allowed to be set, the AETs satisfy 63 out of 100 travel requests and the other two scenarios have a slightly higher number of satisfied requests. However, the charging time of these three scenarios shows a different trend: with more opportunity charging locations allowed, the total and average charging time per AET is decreasing, with a slow speed. This can be explained together with the other indicator: average driving distance. In the first scenario, the AETs driving distance is 36.6 km which is much more than the other two. It is because when there are only a few charging stations distributed in the urban area, the vehicles should travel more to go to the charging station. Nevertheless, if there are more charging stations, the AETs may find one nearby and charge there with little travel distance. The increase of opportunity charging station can help the AET system to decrease the average travel distance but not always. When we allow at most 6 charging stations to be located in the city, the model only decides to select 5 zones as the place for opportunity charging and the average travel distance slightly decreases from 28.4 km to 27.4 km.

(a) Optimal charging locations (a=2)

(b) Optimal charging locations (a=4)

(c) Optimal charging locations (a=6)

FIGURE 3 OPTIMAL CHARGING LOCATIONS FOR VARIATION IN THE NUMBER OF OPPORTUNITY CHARGING LOCATIONS

FIGURE 3 shows the optimal locations for variation in the number of opportunity charging locations. When only two stations are allowed, the model decides to balance the space distribution of the travel demand so one zone on the west side and one zone on the east side are selected. However, this creates extra travel distance since all the travel requests are connected with the train station. When the maximum number of opportunity charging stations grows to 4 and 6, the system has more flexibility to choose locations and the zone of the train station turns to be a selected location. In the last scenario, the model allows to select at most 6 locations but the optimal solution only selects 5 locations for the opportunity charging. This means more charging stations are not needed and the current ones can properly satisfy the AETs' charging demand.

IV. CONCLUSIONS

This paper proposes a mathematical model to plan the optimal location of two types of charging for the shared use AET system. We consider that the AETs can be charged by two kinds of charging infrastructure: depot charging with lower charging speed during the operation pause and opportunity charging with higher charging speed during the operation time. The model is established to maximize the number of satisfied requests considering a fixed fleet size and charging requirements. It can provide an optimal solution about the locations of depot charging and opportunity charging station, as well as the reservations to be accepted.

The model is applied to the case study city Delft, the Netherlands with the last mile travel demand for train trip connection. This case study is with 16 hours' operation time and 100 reserved travel requests within 32 demand zones. From that application, we can take the following conclusions.

The charging scheme with depot charging and opportunity charging can provide electric energy for a shared used AET system for the last mile travel demand. With different charging infrastructure, the AETs will be fully charged by depot charging in the operation pause and during the operation time, the AETs can be charged shortly and frequently with a higher speed to get enough electricity to travel.

The model provides a mathematical way to select the optimal locations for depot charging and opportunity charging regarding the objective to maximize the number of satisfied requests. With a higher fleet size, the AET system can serve more travel requests due to the increase in vehicle and also the initial amount of electrical energy. The number of charging stations is also a critical parameter regarding system performance. With fewer charging stations, the average travel distance will increase when serving the same number of satisfied requests. This is because the AETs should travel more to the charging stations to fill their battery. However, keep increasing the number of charging stations cannot always help improve the satisfying rate, because other key factors may also influence the system, e.g. the fleet size and the time-space distribution of the travel demand.

It is possible to extend the research based on this model for the future. First, we intend to consider a generalized cost of operating the system and to do profit maximization to perform a cost-benefit analysis of the AET system. Second, the riding-sharing can be included to see the impact of taking multiple passengers on route change and charging behaviour.

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