Joint Fleet Sizing and Charging System Planning for Autonomous Electric Vehicles

Hongcai Zhang®, Member, IEEE, Colin J. R. Sheppard, Timothy E. Lipman, and Scott J. Moura®, Member, IEEE

Abstract—This paper studies the joint fleet sizing and charging system planning problem for a company operating a fleet of autonomous electric vehicles (AEVs) for passenger and goods transportation. Most of the relevant published papers focus on intricate scenarios and adopt heuristic approaches, e.g., agent based simulation, which do not guarantee optimality. In contrast, we propose a mixed integer linear programming model for intercity scenarios. This model incorporates comprehensive considerations of 1) limited AEV driving range; 2) optimal AEV routing and relocating operations; 3) time-varying origin-destination transport demands; and 4) differentiated operation cost structure of passenger and goods transportation. The proposed model can be computational expensive when the scale of the transportation network is large. We then exploit the structure of this program to expedite its solution. Numerical experiments are conducted to validate the proposed method. Our experimental results show that AEVs in passenger and goods transportation have remarkable planning and operation differences. We also demonstrate that intelligent routing and relocating operations, charging system and vehicle parameters, e.g., charging power, battery capacity, driving speed etc., can significantly affect the economic efficiency and the planning results of an AEV fleet.

Index Terms—Autonomous vehicle, electric vehicle, fleet size, charging system planning, routing, relocating.

I. INTRODUCTION

Autonomous driving is believed to be a disruptive technology that will transform our transportation system in the near future. Autonomous vehicles (AVs) that transport passengers or goods without human intervention will not only free human drivers from burdensome driving labor, but also promote transportation accessibility [1], cut down mobility costs [2]–[4], enhance energy efficiency, and reduce greenhouse gas emission [5]–[8]. When AVs are electrified, which we refer to as autonomous electric vehicles (AEVs), then the last two aforementioned advantages will be further enhanced, particularly if the electricity is supplied from clean energy (e.g., renewable power generation) [9].

Passenger (e.g., ride-hailing) and goods transportation are clear initial markets for AEV fleets. Specifically, they feature high utilization levels and planned routes, which can exploit the aforementioned advantages of AEVs [10], [11]. Hence, it is soon possible for transportation network companies, e.g., Uber and Lyft, or logistics companies, e.g., UPS and DHL, to operate a fleet of AEVs in their businesses.

In this paper, we focus on the planning problem of AEVs for these businesses in intercity transportation. We envision that, with AEVs, transportation network companies may also launch services to satisfy passenger transportation demands across cities, e.g., autonomous electric intercity buses. As a result, they may face similar problems with logistics companies. We will uniformly refer to them as AEV operating companies.

An AEV operating company needs to solve the following problems before launching its business:

1) Fleet sizing, i.e., size an AEV fleet to satisfy given transport demands. On one hand, though vehicle automation allows companies to hire less human drivers to save labor costs, AVs could be very expensive especially in the early stage of commercialization. On the other hand, high automation allows the company to dispatch and route AEVs more efficiently leading to much higher vehicle utilization. Thus, a company needs to optimally design its AEV fleet size to fully exploit AEVs’ potential and reduce its costs considering future strategic operations.

2) Charging system planning, i.e., locate EV chargers to satisfy charging demands. Compared with traditional internal combustion vehicles, EVs generally have much higher fuel efficiency, thus will significantly reduce a company’s fuel costs. However, the company may also need to invest in sufficient charging infrastructure to charge the AEVs [12]. This can be vitally important for the early stage of transportation electrification when public fast chargers are not quite popularized, especially on intercity corridors.

The above two problems are highly coupled together because the planning of charging systems can impact the utilization of AEVs: 1) charging can lead to significant “down time” 1; 2) AEVs may detour to get charged when chargers are not available.

1 Because the rated charging power is not high enough.
available on their preferred paths or the charging prices elsewhere are cheaper so that vehicle miles traveled may increase.

As a result, it is necessary for a company to jointly design its fleet size and charging system according to the expected transportation demands. It is also important to carefully consider the routing and charging operations in the design solution.

Both AV fleet sizing and EV charging system planning have been active areas of research for years. Many researchers have studied these two problems separately, summarized as follows.

High automation of AVs means they have the potential to satisfy more demands than the same number of human-driven vehicles. Hence, many researchers have studied the AV fleet sizing problem to evaluate their economic advantages. Boesch et al. [13] proposed an agent-based simulation approach for the fleet sizing problem of shared-use AVs based on which the authors evaluated how the AVs’ service level could affect the required fleet size. Alonso-Mora et al. [14] developed a dynamic trip-vehicle assignment strategy for autonomous ride-sharing services and studied the trade-off between the fleet size and the performance of the ride-sharing service. Fagnant and Kockelman [15] developed an agent- and network-based simulation framework that considers dynamic ride-sharing and vehicle relocation to estimate fleet size and operator profitability for given demands. Vazifeh et al. [16] provided a network-based solution to the fleet sizing problem to determine the minimum number of vehicles needed to serve given trips without incurring any delay to the passengers.

Limited driving range is the major hurdle for EV application. The charging system planning problem has been extensively studied in the literature. Generally, the published approaches can be divided into three categories: 1) computational geometry based approaches that assume charging demands occur on geographical nodes and ignore transportation network structure [17]–[20]; 2) simulation- or data-driven approaches [21]–[24], which adopt agent-based simulation or real-world data to estimate future EV charging behaviors; 3) Origin-Destination (OD) flow based methods that explicitly describe transportation network constraints, i.e., driving range constraints [25]–[31]. The first two categories are popular for EV charging station planning in intracity scenarios where transportation networks are too complex to deterministically describe. The third category is widely used in intercity scenarios where transportation networks are comparatively simple, which makes explicitly describing EVs’ range constraints possible. Because that EV charging systems are coupling power and transportation networks together, many researchers have proposed multidisciplinary approaches to plan charging systems in coupled networks [32]–[41].

However, there are only a few papers that have addressed the joint AV fleet sizing and charging system planning problem. Hiermann et al. [42] studied the EV fleet sizing and routing problem including the choice of recharging times and locations. They took the design of EV charging stations as given. Chen et al. [43] proposed an agent-based simulation platform to size shared-use AEVs. Based on the platform, they evaluated various charging infrastructure investment decisions. Bauer et al. [44] designed an agent-based simulation framework to estimate required fleet size and most economic charging systems to satisfy taxi-hailing demands. Dandl et al. [45] compared fleet size requirement and profitability of an AEV taxi fleet with an existing free-floating carsharing system based on a data-driven simulation approach.

None of the above papers have addressed the intercity scenarios of AEV application. Most of the proposed approaches are based on simulation and heuristic optimization techniques because the transportation networks in intercity scenario are too complex to deterministically describe. Besides, most of the papers focus on passenger transportation while AEVs may behave quite differently when they are used for goods transportation: For the former, it is necessary to drop the passenger to the destination in time because the passenger’s time is quite valuable; however, for the latter, an AEV has lower time cost so that it will be willing to detour more so that it can get cheaper electricity or avoid congested charging stations [46]. A comparison on the operation costs between passenger and goods transportation is given in Table I. The loaded trips are with passengers or goods, while the relocating ones are empty AEVs relocating from one location to another.

To address the aforementioned problem, we propose a joint fleet sizing and charging system planning model to help AEV operating companies to right-size their AEV fleets and design charging infrastructure at least cost while meeting their transport demands in intercity corridors. This paper advances the relevant literature by the following contributions:

1) A joint AEV fleet sizing and charging system planning model that simultaneously optimizes the fleet size and charging system to satisfy a mobility on demand system is developed. The planning model takes the strategic routing and relocating of AEVs into consideration so that it can balance the investment costs at the planning stage and the operation costs in the future. Furthermore, both passenger and goods transportation can be modeled.

2) The limited driving range constraints of AEVs are explicitly described by an expanded transportation network model based on OD transport demands. The impact of vehicle charging behaviors on fleet operation and charging system planning can be effectively evaluated.

3) The proposed model is a mixed integer linear program that can be computationally expensive when the scale of the transportation network is large. We exploit the

<table>
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<tr>
<th>Case</th>
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<th>Fuel costs</th>
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<td>Relocating</td>
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It should be noted that we assume there is no time window constraint for good transportation in this paper. In practice, this assumption may not hold. As a result, the AEVs will not be able to detour too much so that their behaviors will be similar with those with passengers.
structure of the program so that we can remove part of the feasible region and expedite its solution significantly with guaranteed solution quality.

In addition, numerical experiments are conducted to validate the proposed method. The results show that AEVs in different application scenarios, i.e., passenger and goods transportation, have fundamental planning and operation differences. We also demonstrate that intelligent relocating operation and system and vehicle parameters, e.g., charger power, battery capacity, driving speed etc., all can significantly affect the economic efficiency of an AEV fleet and the planning results.

We briefly introduce the expanded transportation network model in Section II. Section III formulates the complete planning model. We exploit the structure of the model and propose a solution approach in Section IV. Numerical experiments are presented in Section V. Section VI concludes the paper.

II. EXPANDED TRANSPORTATION NETWORK MODEL

This section introduces an expanded transportation network model that describes AEVs’ driving range constraints. This model originates from the flow-refueling location model developed by Kuby and Lim [47] that assumes AEVs’ driving paths are fixed. This proposed model extends it by allowing AEVs to choose different paths to drive from an origin to its destination. We consider a scenario that one company owns and operates the AEVs to provide transportation services and all the AEVs in the system are homogeneous. To construct a computational efficient transportation network model with driving range constraints, we assume that: 

[A1]: AEVs will get fully charged charging stations.

[A2]: The routing of AEVs will not affect traffic conditions, so the driving speed on each arc is exogenously defined.

We use a directed graph G(I, A) to model the transportation network, where I denotes node set and A denotes arc set. An arc (i, j) ∈ A is the road link between two adjacent nodes, i ∈ I and j ∈ I. Symbol l_{ij} is the length of arc (i, j). We use OD pairs to model transport demands. An OD pair (indexed by g) is composed by an origin node o_g ∈ I and a destination node d_g ∈ I. The transport demands in one OD pair g is denoted by tuple (o_g, d_g, i^od_g), ∀g ∈ G. Symbol i^od_g represents the Poisson volume of demands from origin node o_g to destination node d_g. We call the route that an AEV can choose from an origin to a destination as a path.

3Note that though we did not consider vehicle heterogeneity in this paper, our method can be readily extended to consider it, which will be our future work. We will discuss this in the Conclusion Section.

4In practice, a typical EV charging process usually includes two stages: 1) the constant current charge, when the battery is charged around its rated charging power; 2) the constant voltage charge, when the charging power decreases gradually to top off batteries [48]. Considering that the second stage is slow, we assume the AEVs only get charged at the first stage to save time. Hence, we use “fully charged” to describe that an AEV gets charged till the end of the constant current stage instead of charging its SoC to 100%.

5There is usually significant fixed time cost for an AEV to use a charging station, it will not tend to get partially charged each time. Besides, when this assumption does not hold, the planning model based on it will provide a conservative investment decision, which will still be feasible in practice.

6This assumption may be realistic when the majority of vehicles on road are highly automatic and intelligent so that the network is rarely congested, or the penetration of AEVs in the vehicles on road is small so that they have negligible impacts on traffic conditions.

### A. Transportation Network Expansion

We take a simple transportation network G(I, A) in Fig. 1(a) as an example. It only has a single OD pair, g = (o, d). There are two paths that the AEVs can travel from origin node o to destination node d, i.e., path (o1534d) and path (o1234d). The AEV transport demand in this network is (o, d, i^od). The AEVs’ driving range is R = 100 km. The average driving speeds on different arcs are the same.

We can expand the network G(I, A) in Fig. 1(a) into a new network G(I, ˆA) in Fig. 1(b) by the following steps:

1) Connect any two nodes, say i and j, in I, by a pseudo arc if node j can be reached from node i after a single charge. Let each new arc’s direction be consistent with the traffic flow direction of the original network.

2) Let the lengths of the pseudo arcs defined in step 1) be equal to those of the corresponding two nodes’ shortest paths. For example, i_{o2} = l_{i1} + l_{12}. For arc (1, 3), an AEV may drive through it by path (123) or (153). However, under Assumption [A2], an AEV driving from node 1 to node 3 without getting charged between them will only choose the shortest path (123) to minimize its costs. Therefore, we can let i_{13} = l_{12} + l_{23}.

3) Let set ˆA be the union of A and the pseudo arcs added in step 1). Then, we have the expanded network G(I, ˆA).

In the expanded network G(I, ˆA), each path from o to d characterizes a feasible solution for an AEV with driving range R to drive from node o to d on the condition that whenever it runs across a node in I it gets charged. For example, an AEV can travel through path (o24d) if it gets charged at nodes 2 and 4; and it can also travel through path (o53d) if it gets charged at nodes 3 and 5. In summary, this expanded transportation network model incorporates AEV driving range constraints.

Note that under assumptions [A1] and [A2], when an AEV does not get charged between two nodes i and j, it will only choose the shortest path (with minimum time or costs) to drive from i to j, rendering a unique pseudo arc (i, j). Thus, given
the original transportation network, the expanded network can be uniquely determined a priori offline and the cardinality of the arc set in the expanded network is limited by $|I|^2$. Furthermore, the energy consumption and driving time on each arc can also be estimated a priori based on the arc length.

B. Traffic Flow Continuity Constraints

For each transport demand $(o_g, d_g, \lambda_{od_g})$, $\forall g \in G$, it may traverse any arc and node in the transportation network. The inflow and outflow should balance at each node. Besides, the traffic flow from each origin node and each destination node should be equal to the total transport demand. These constraints can be represented as follows:

$$
\sum_{(j | (i, j) \in \hat{A})} \lambda_{g,ij} - \sum_{(k | (k, i) \in \hat{A})} \lambda_{g,ki} = \begin{cases} 
\lambda_{od_g}, & \text{if } i = o_g \\
-\lambda_{od_g}, & \text{if } i = d_g \\
0, & \text{if } i \neq o_g, d_g 
\end{cases} 
\forall g \in G, \forall i \in I, \quad (1)
$$

where $\lambda_{g,ij}$ is the portion of AEV flow driving on arc $(i, j)$ corresponding to demand $(o_g, d_g, \lambda_{od_g})$. Note that the AEVs in $\lambda_{g,ij}$ also get charged in the charging station at node $j$.

III. FLEET SIZING AND CHARGING SYSTEM PLANNING

In this section, we formulate a joint AEV fleet sizing and charging system planning model, which optimally determines the AEV fleet size and the capacities of AEV charging stations in the transportation network. The nomenclature of this model is summarized in Table II. We consider time-varying traffic flow and adopt tuple $(o_g, d_g, \lambda_{od_g}, t)$ to denote the transport demands, which means there are $\lambda_{od_g}$ demands that need to depart from origin $o_g$ during hour $t$ to destination $d_g$.

The proposed model considers “relocation” of autonomous AEVs to fully utilize their automation potential:

1) When an AEV arrives at its destination, it can be used to satisfy another demand that originates from its destination right after it gets fully charged.

2) An idle AEV can also be moved to other transportation nodes to satisfy future demands there, which is referred to as “relocation” in this paper.

Hereafter, we call the driving AEVs loaded ones if they are with passengers or goods and relocating ones otherwise.

To construct a computational efficient model and avoid comprehensive and intractable modeling of multiple-trip AEV driving range constraints, we make the following assumption:

[A3]: An AEV will get fully charged when it arrives at a destination before it can be scheduled for the next trip.7

We begin with a base model for passenger transportation, in which a loaded AEV has significant passenger time costs while a relocating one does not as indicated in Table I. Then, we will show how the model can be modified when the cost factors for loaded and relocating AEVs are similar in goods transportation scenarios.

7This assumption can be true when each trip is long enough in intercity corridors. With it, we will make a conservative planning result so that the system can be more robust.

A. Objective

The objective of the model is to minimize the total costs including the investment for AEV fleet and charging stations, the operation costs for both time, electricity and maintenance.

1) Investment Costs for AEVs & Charging Systems: The investment costs for purchasing AEVs and installing charging
stations can be calculated as follows:

\[ c^{ev}_x + \sum_{i \in \mathcal{I}} c^{sp}_{ij} y_i, \]  
(3)

where \( x \) is the fleet size and \( y_i \) is the number of chargers at node \( i \). Symbols \( c^{ev} \) and \( c^{sp} \) are the per-unit cost for one AEV and one charger at location \( i \), in \$, respectively.\(^8\)

2) Operation Costs for Time, Electricity and Maintenance: The operation costs of the AEV system are mainly composed by passenger time, electricity consumption, and maintenance. The total time that a loaded AEV spends on one arc \((i, j)\) includes two parts: 1) the driving time, \( t^{\text{drive}}_{ij} \), and 2) the charging time at the station, \( t^{\text{charge}}_{ij} \). In terms of costs, only the passenger’s time is valuable, while an AEV without a passenger has no time cost. We adopt \( t_{g,ij} \) to denote the time that a passenger spends on arc \((i, j)\) in OD pair \( g \). Then, it is:

\[ t_{g,ij} = t^{\text{drive}}_{ij} + (1 - d_{g=j}) t^{\text{charge}}_{ij}, \]

\[ = \frac{\xi_l}{v} + (1 - d_{g=j}) \frac{\xi_l}{\eta p^{sp}}, \quad \forall (i, j) \in \hat{A}, \forall g \in \mathcal{G}, \]  
(4)

where symbol \( v \) represents the AEVs’ average driving speed, in km/h; \( \xi \) is the fuel efficiency, in kWh/km; \( \eta \) is the charging efficiency; \( p^{sp} \) is the rated charging power, in kW. Hence, \( \xi_l \) is the total electricity that an AEV consumes on arc \((i, j)\). Symbol \( 1 - d_{g=j} \) represents whether arc \((i, j)\)’s end node \( j \) is also the AEV’s destination \( d_{g} \): \( 1 - d_{g=j} = 1 \), if it is; \( 1 - d_{g=j} = 0 \), otherwise. Because when a loaded AEV arrives at its destination, it will drop the passenger first before getting charged. Hence, a passenger does not spend any charging time after arriving at its destination (denoted by the last term in (4)).

We assume that the time, electricity and maintenance costs are, respectively, proportional to the time a passenger spends on arc \((i, j)\). Since the electricity cost is location dependent, we assume the passenger spends on arc \((i, j)\) in OD pair \( g \) can be calculated as follows:

\[ c^{\text{oper}}_{g,ij} = c^{\text{time}}_{g,ij} + c^{\text{el}}_{ij} + c^{\text{ma}}_{ij}, \quad \forall (i, j) \in \hat{A}, \forall g \in \mathcal{G}, \]  
(5)

where symbols \( c^{\text{time}} \), \( c^{\text{el}} \) and \( c^{\text{ma}} \) are the per-unit passenger time cost, in \$/hour, per-unit electricity cost, in \$/kWh, and per-unit maintenance cost, in \$/km, respectively. Note that the electricity costs are location dependent (affected by the locational marginal electricity prices [49]) due to unbalanced power supply capabilities.\(^11\)

3) Total Objective: In summary, the annual expected total investment and operation cost can be formulated as follows:

\[ \text{Obj} = \min \sum_{i \in \mathcal{I}} c^{ev}_i + \sum_{i \in \mathcal{I}} c^{sp}_{ij} y_i + 365 \sum_{g \in \mathcal{G}} \sum_{(i, j) \in \hat{A}} \left( c^{\text{time}}_{g,ij} + c^{\text{el}}_{ij} + c^{\text{ma}}_{ij} \right) \lambda_{g,ij}, \]  
(6)

where \( \zeta \) is the capital recovery factor, which converts the present investment costs into a stream of equal annual payments over the specified lifespan at the given discount rate; \( \lambda_{g,ij} \) are, respectively, the fraction of loaded and relocating AEVs on arc \((i, j)\) in OD pair \( g \) that depart during hour \( r \). In the objective, the first and second terms are investment costs for the AEV fleet and charging stations, respectively; the third and fourth terms are the operation costs for the loaded and relocating AEVs, respectively.\(^12\) The former has time costs while the latter does not.\(^13\)

B. Constraints

This sub-section describes the constraints of the planning model. In summary, the dispatch of loaded and relocating AEVs shall be able to satisfy the transport demands and subject to the physical transportation network constraints described in Section II. To better evaluate the demands for AEVs, we adopt constraints to describe the dynamics of AEV departure, arriving, and parking. In addition, the total fleet size shall be no less than the total number of AEVs driving or parking on the network during any hour, and the installed chargers shall be able to satisfy the peak charging demands at each location.

1) AEV Traffic Flow Continuity: The distribution of the AEV traffic flow should satisfy the transportation network constraints indicated by the expanded network model (1)–(2). In the proposed model, the total AEVs on each path includes the loaded AEVs to satisfy the OD transport demand and the relocating ones. Hence, the expanded network model can be extended to consider this fact. However, we omitted it for brevity.

\(^8\)In this paper, we assume the investment cost for a charging station is linear to the number of chargers. In practice, this may be not true. We can then 1) take the estimated average per-unit cost for the planning; or 2) adopt piecewise linear model to approximate the nonlinear model.

\(^9\)In practice, this charging time may also include an estimated waiting time. Besides, there may be also extra time due to vehicle stop, passenger service, or loading/unloading for goods transportation. We assume they are negligible compared with driving and charging time. Nevertheless, they can be estimated a priori and included in the driving time when necessary.

\(^10\)We assume that the fuel efficiency \( \xi \) is homogeneous across the transportation network in this paper. In practice, different arcs may have different fuel efficiency depending on road conditions. It is trivial to extend our model to consider this fact. Hence, we omitted it for brevity.

\(^11\)In practice, the electricity price may also be time-varying. Our model can be trivially extended to consider this fact by substitute the static charging price parameter with a time-varying one.

\(^12\)In practice, the trip demand in the future are uncertain. Though we assumed the demands are given in this paper, our method can be readily extended to consider stochastic demands. One typical approach is the two-stage stochastic programming, e.g. in reference [20]. We can adopt a number of representative scenarios to represent the future demands. Then, solve the optimization problem to minimize the summation of total investment costs and the expected average operation costs.

\(^13\)In practice, loaded and relocating AEVs may also have different fuel efficiency. It is trivial to extend our current model to consider this fact.
where $\lambda_{g,i,t}$ and $\lambda_{g,i,t}^{opt}$ are the transport demands and relocating AEVs in OD pair $g$ departing in hour $t$, respectively. Symbol $\lambda_{g,i,t}$ is the loaded AEV traffic flow on arc $(i,j)$ of the expanded network; $\lambda_{g,i,t}^{rel}$ is the corresponding relocating AEVs on arc $(i,j)$. Note that the transport demand $\lambda_{g,i,t}^{opt}$ is given, while the relocating flow $\lambda_{g,i,t}^{rel}$ is a decision variable.

2) Relationship Between AEVs on Arcs and on Paths: Assuming that the loaded or relocating AEVs corresponding to demands $(\alpha_g, d_g, \lambda_{g,i,t}^{opt})$ will only choose the paths in the set $Q_g$ or $Q_e$, $\forall g \in G$, respectively. Then, the relationship between AEVs driving on paths and on arcs are:

$$\lambda_{g,i,t} = \sum_{q \in Q_g} 1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} \forall g \in G, \forall (i,j) \in A, \forall t,$$ (10)

$$\lambda_{g,i,t}^{rel} = \sum_{q \in Q_g} 1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} \forall g \in G, \forall (i,j) \in A, \forall t,$$ (11)

$$\lambda_{g,q,t}^{path} \geq 0, \forall g \in G, \forall q \in Q_g, \forall t,$$ (12)

$$\lambda_{g,q,t}^{path} \geq 0, \forall g \in G, \forall q \in Q_e, \forall t,$$ (13)

where $1_{(i,j) \in A_g} = 1$ if arc $(i,j)$ is on path $q$; $1_{(i,j) \in A_g} = 0$, otherwise. Based on equations (10)–(13), we can substitute decision variables $\lambda_{g,i,t}$ and $\lambda_{g,i,t}^{rel}$ by $\lambda_{g,q,t}^{path}$ and $\lambda_{g,q,t}^{path}$. If we are able to find small scale path sets, $Q_g$ or $Q_e$, $\forall g \in G$, that cover the paths that AEVs will adopt, the scale of the decision variables can be significantly reduced. Section IV will discuss how to reduce the complexity of the problem by exploiting the structure of the problem based on these relationships.

3) AEV Departure & Arrival Time: As discussed in Section II, an AEV’s total driving and charging time on any path $q$, i.e., $\tau_q$, can be easily calculated a priori based on arc length, average driving and charging speed. Hence, there is a unique mapping between AEVs departing from the origin, $\lambda_{g,i,t}$, and AEVs arriving at destination, $\lambda_{g,i,t}$, between different hours on each path. This can be described as follows:

$$\lambda_{g,i,t}^{dep} = \sum_{q \in Q_g} \lambda_{g,q,t}^{path} + \sum_{q \in Q_e} \lambda_{g,q,t}^{path} \forall g \in G, \forall t,$$ (14)

$$\lambda_{g,i,t}^{arr} = \sum_{q \in Q_g} \lambda_{g,q,t}^{path} - \tau_q + \sum_{q \in Q_e} \lambda_{g,q,t}^{path} \forall g \in G, \forall t,$$ (15)

4) AEV Driving on Road: Based on the above analysis on AEV departure and arriving time on paths, it is straightforward to calculate the number of AEVs on roads, as follows:

$$\lambda_{g,q,t}^{drive} = \sum_{g \in G} \left( \sum_{q \in Q_g} 1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} \right) \forall g \in G, \forall t,$$ (16)

$$\lambda_{g,q,t}^{drive} = \sum_{g \in G} \left( \sum_{q \in Q_g} 1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} \right) \forall g \in G, \forall t,$$ (17)

where $1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} = 1$ if the AEVs on path $q$ are driving between time $[t_0, t_0 + \tau]$; $1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} = 0$, otherwise.

5) AEV Parking Dynamics: In practice, the AEV fleet operator may initially locate a number of AEVs at each location for future demands. During the operation, the number of vehicles parking at each node will change. The corresponding dynamics can be represented as follows:

$$\lambda_{i,t}^{park} = \lambda_{i,t}^{park} + \sum_{g \in G} \left( \sum_{q \in Q_g} 1_{(i,j) \in A_g, \lambda_{g,q,t}^{path}} \right) \forall g \in G, \forall t,$$ (18)

$$\lambda_{i,t}^{park} \geq \lambda_{i,0}^{park}, \forall i \in I, \forall t,$$ (19)

$$\lambda_{i,t}^{park} = \sum_{i \in I} \lambda_{i,t}^{park}, \forall t,$$ (20)

where symbol $\lambda_{i,t}^{park}$ denotes the number of AEVs parking at node $i$ during hour $t$; $\lambda_{i,0}^{park}$ represents the initial number of AEVs that are located at node $i$, which is also a decision variable for the system operator. Equations (17) and (22) calculate the AEVs that arrive at and depart from node $i$ during hour $t$, respectively. Equation (17) determines the relationship between numbers of AEV parking, arrival and departure. To avoid myopic fleet relocating, we use equation (18) to require that the number of parking AEVs at each node will return to the corresponding initial value after the operation period, $T$, e.g., one day. Equation (19) constrains the maximum number of AEVs parking at each location due to parking space limitation, in which symbol $\lambda_{i,max}^{park}$ denotes the upper bound. Symbol $\lambda_{i,t}^{park}$ represents the total number of parking AEVs during hour $t$, which is calculated by (20).

6) AEV Fleet Size: The total number of AEVs should be higher than the summation of those parking and driving:

$$x \geq \lambda_{g,q,t}^{drive} + \lambda_{g,q,t}^{park}, \forall t,$$ (21)

7) AEV Charging Station: At each node $j$, there should be enough chargers to guarantee adequate quality of service:

$$y_j \geq \alpha \sum_{g \in G} \sum_{(i,j) \in A_g} \frac{\xi_{ij}}{\eta_{pp}} \left( \lambda_{g,i,j} + \lambda_{g,j,i}^{rel} \right), \forall j \in J,$$ (22)

where $\frac{\xi_{ij}}{\eta_{pp}}$ is the required charging time of an AEV on arc $(i,j)$. Symbols $\lambda_{g,i,j}$ and $\lambda_{g,j,i}^{rel}$ represent the loaded and relocating AEV flow on arc $(i,j)$ during the peak hour, respectively. Symbol $\alpha$ is a coefficient that is higher than 100% to make the planning slightly conservative. When $\alpha = 100\%$, $y_j$ is the number of chargers to satisfy the mean demands.
C. Complete Fleet Sizing & Charging System Planning Model

The above formulations form the joint AEV fleet sizing and charging station planning model for passenger transportation:

\[ \text{P1: } \min (6) \quad \text{s.t.: (7)} - (22). \]

Because that variables \( x \) and \( y \) are integers, the above problem is a mixed-integer linear program.

For goods transportation, neither loaded nor relocating AEVs have passengers or drivers, hence, there will be no time cost for them. The objective in (6) is modified as:

\[
\begin{align*}
\text{Obj} &= \min \left( \zeta c^p + \zeta \sum_{i \in I} c^p y_i \right) \\
&+ 365 \sum_{g \in G} \sum_{(i,j) \in A} \sum_{\tau} \left( c^g_{ij} \frac{\xi}{\eta} + c^{ma} \right) \\
\times l_{ij} \left( \lambda_{g,ij,\tau} + \lambda^{rel}_{g,ij,\tau} \right). 
\end{align*}
\]

(23)

Hence, the joint AEV fleet sizing and charging station planning model for goods transportation is summarized as follows:

\[ \text{P2: } \min (23) \quad \text{s.t.: (7)} - (22). \]

Note that without time cost in goods transportation, an AEV may detour more in order to get charged at lower electricity prices or allow the system to install less chargers. However, long driving and charging time will still affect an AEV’s utilization so that it will not detour unrestrained.

IV. Solution Approach

Because an AEV may theoretically choose any path available to travel between any OD pair in the network, the proposed model \( \text{P1} \) can be computationally expensive when the network is large. However, in practice, the choices of an AEV between one OD pair can be quite limited because detouring from the shortest path to other ones could be expensive due to high time, electricity and maintenance costs. Therefore, if we are able to find the smallest path sets \( \mathcal{Q}_g \) and \( \mathcal{Q}^{rel}_g \), \( \forall g \in G \), in equations (10)–(11) that contain all the paths that will be used by AEVs, we can reduce its complexity significantly without sacrificing any optimality.

Finding these path sets is challenging. Nevertheless, in this section, we propose some superset sets of \( \mathcal{Q}_g \) and \( \mathcal{Q}^{rel}_g \), \( \forall g \in G \), by exploiting the structure of this problem to eliminate redundant paths that are not likely to be used by AEVs between each OD pair. Utilizing the proposed superset sets can significantly reduce the computational efficiency of the problem \( \text{P1} \) without sacrificing optimality. Furthermore, we also propose subsets of the aforementioned superset sets to approximately solve the problem by tuning a confidence factor of the approximation to balance computational efficiency and optimality. As a result, the problem can be still tractable in large-scale networks with guaranteed solution quality.

A. Eliminating Redundant Paths for Loaded AEVs

1) Warm-Up Solution: First, we ignore the investment costs for AEV fleet and charging systems or assume that they are negligible compared to operation costs. Then, an AEV will only choose the path that minimizes its operation costs between an OD pair, which is referred to as the min-operation path hereinafter. As a result, each OD pair only corresponds to one path so that the planning problem will reduce to a small scale problem that can be efficiently solved by an off-the-shelf solver. However, the result may be sub-optimal when operation costs are not dominating the system or the company has limited budget and hopes to save its investment costs.

We will adopt the above solution with min-operation paths as a warm-up based on which we will exploit the structure of the problem and eliminating redundant paths for the OD pairs to reduce problem complexity.

2) Eliminating Redundant Paths Based on Fleet Size: For the fleet sizing problem, when an AEV is driving or charging, it is not available for relocating or servicing other demands. Hence, any time delay caused by detour may lead to opportunity cost for investing in a larger fleet. Therefore, it is possible to reduce the system’s total costs by routing some AEVs to drive on paths with shorter time rather than min-operation paths.

We use \( q \) to denote the index of paths between one OD pair \( g, q \in \mathcal{Q}_g; 0 \) to denote the index of the min-operation path. Let \( \mathcal{A}_g \) denote the set of the arcs on path \( q \). Then, if a fleet of AEVs, \( \lambda \), drive on path \( q \), the incurred operation costs are:

\[
C_q = 365 \sum_{(i,j) \in \mathcal{A}_g} \left( c^{time} t_{g,ij} + c^{el} \frac{\xi_{ij}}{\eta} + c^{ma} \right) \lambda. 
\]

(24)

Note that for goods transportation, \( c^{time} = 0 \). The total driving and charging time on path \( q \) is \( t_q = \sum_{(i,j) \in \mathcal{A}_g} t_{g,ij} \).

Based on the above analysis, when we ignore the investment costs in charging systems, we have the following proposition:

Proposition 1: The maximum total system cost reduction for \( \text{P1} \) when \( c^p = 0 \) by detouring \( \lambda \) AEVs from min-operation path 0 to any other path \( \forall q \in \mathcal{Q}_g \setminus \{0\} \) is upper bounded by:

\[
\Delta C_{q,1} = \begin{cases} 
C_0 - C_q, & \text{if } t_q \geq t_0 \\
C_0 - C_q + \zeta c^{ev} \lambda, & \text{if } t_q < t_0.
\end{cases}
\]

(25)

Proof: The proof for this proposition is intuitive: 1) When \( t_q \geq t_0 \), detouring one AEV from path 0 to path \( q \) will not reduce the fleet size because the AEV will arrive at its destination later than before. Hence, the total system cost will at least increase by \( C_q - C_0 \geq 0 \). 2) When \( t_q < t_0 \), \( \lambda \) AEVs will arrive at their destination and be able to service other demands earlier. The most optimistic scenario is that the earlier arrived AEVs happen to satisfy the gap between demands and supply at that location during that specific time interval so that \( \lambda \) AEVs can be saved. Hence, the maximum possible cost reduction is the difference between the saved fleet investment \( \zeta c^{ev} \lambda \) and the operation cost increment due to detouring \( C_q - C_0, \) i.e., \( C_0 - C_q + \zeta c^{ev} \lambda \).

Remark 1: Based on Proposition 1, an AEV may only choose a path \( q \) when \( \Delta C_{q,1} > 0 \). Hence, all other paths can be eliminated.

3) Eliminating Redundant Paths Based on Charging Systems: Similarly, we can also eliminate redundant paths based...
on charging system investments. If we ignore the fleet investment costs, we have:

**Proposition 2:** The maximum total system cost reduction for $P_1$ when $c^\text{ev} = 0$ by detouring $\lambda$ AEVs from min-operation path 0 to any other path $g \in Q_g \setminus 0$ is upper bounded by:

$$\Delta C_{g,2} = C_0 - C_g + \xi c_i^{\text{sp}} \alpha \sum_{(i,j)\in \hat{A}_0^g} \frac{\xi l_{ij}}{\eta p_{ij}} \lambda,$$

(26)

where set $\hat{A}_0^g = \hat{A}_0 \setminus (\hat{A}_0 \cap \hat{A}_g)$ represents the arc set on path 0 that the AEVs will no longer visit after detouring so that the corresponding charging demands will be satisfied elsewhere.

**Proof:** The proof for Proposition 2 is also intuitive: after detouring, only those chargers that are installed on arcs in $\hat{A}_0^g$ that are no longer visited by fleet, $\lambda$, may be saved.

Remark 2: Based on Proposition 2, an AEV may only choose path $q$ when $\Delta C_{q,2} > 0$. Thus, all other paths can be eliminated.

4) **Eliminating Redundant Paths for Relocating AEVs**

**Proposition 3:** The maximum total system cost reduction for $P_1$ by detouring $\lambda$ AEVs from min-operation path 0 to any other path $g \in Q_g \setminus 0$ is upper bounded by:

$$\Delta C_g = \begin{cases} C_0 - C_g + d, & \text{if } t_g \geq t_0 \\ C_0 - C_g + \xi c^{\text{ev}} \lambda + d, & \text{if } t_g < t_0, \end{cases}$$

(27)

where $d = \xi c_i^{\text{sp}} \alpha \sum_{(i,j)\in \hat{A}_0^g} \frac{\xi l_{ij}}{\eta p_{ij}} \lambda$.

To avoid considering all paths (which is time-consuming and unnecessary), we leverage the $k$ shortest path routing algorithm [50]. In it, up to $k$ paths with the least operation costs are identified in sequence whose operation costs monotonically increase. We initially set $k$ as a large enough number, and stop identify new paths when the most recently identified path has $\Delta C_g \leq 0$ (the remaining paths will all have $\Delta C_g \leq 0$). Then, we use all the identified paths to construct the superset of $Q_g$, $\forall g \in G$. As a result, we don’t need to check all the possible paths. Instead, we need only consider these super path sets in the optimization model so that the problem scale can be significantly reduced and optimality is still retained.

If the supersets are still too huge due to the network’s large scale, we can remove all the paths that have $\Delta C_g \leq \text{gap} \times \text{obj}_{g_{\text{obj}}}$, where $\text{obj}_{g_{\text{obj}}}$ is the total objective value of the warm-up solution, and $\text{gap}$ is a confidence factor. Apparently, by letting $\text{gap} > 0$, we are able to reduce the number of paths remaining in the path sets, which may result in a sub-optimal solution. By adjusting $\text{gap}$’s value, we can balance computational efficiency with optimality of the problem effectively.

The above proposed approach compensates the column-generation procedures that are popular for solving network flow problems [51]. In a column generation algorithm, the paths are usually also identified and added to the optimization model iteratively. But because that the optimization model is repetitively solved for each iteration until it converges, it may be computationally expensive. In contrast, our proposed algorithm identifies the paths iteratively but solve optimization model for only once. Comparing the proposed algorithm with the column generation approaches is an interesting topic, but is out the scope of this paper, which will be our future work.

**V. CASE STUDIES**

This section considers a 25-node transportation network (see Fig. 2) to illustrate the proposed planning method. The gravity spatial interaction model was used to generate a time varying OD demands based on node weights and arc distances [52].
The lifetime. Therefore, we only use 60 kWh battery capacity to save time; 3) Thirdly, the fuel efficiency of an AEV gets high so that an AEV will not tend to get fully charged. However, we will not model the driving range constraints of AEVs to their initial states after one day of operation. Because of congestion in power networks, the electricity supply costs in different areas may also be different [49]. Hence, we assume heterogeneous electricity prices across the transportation network, i.e., 0.12 $/kWh at nodes 6-8, 11-13, 16; 0.20 $/kWh at nodes 10, 14, 21-25, and 0.30 $/kWh at other nodes.

A. Parameter Settings

We utilize the AEV and charger cost parameters published by Bauer et al. [44]. The per unit cost to purchase an AEV is $c^{ev} = 30,000 + 200B$, in $, where $B$ is the AEV’s battery capacity, in kWh; The per unit cost to install a charger is $c^{sp} = (700 + 15Y) p^g$, where $Y$ is the life time of a charger, in year, $p^g$ is the rated charging power, in kW. The vehicle efficiency $\xi = 0.155 + 0.00037/B$, in kWh/km. The maintenance cost $c^{ma} = 0.025$ kWh/km. We also assume the per-unit time cost for a passenger is $c^{time} = 22.62$ $/hour, which is the average hourly earnings of private-sector production and nonsupervisory employees in the US [53]. The charging efficiency $\eta = 0.92$, the capital recovery factor $r = 0.08$ [39]. We assume the rated charging power of a charger is $p^g = 100$ kW[14] and the average driving speed is 100 km/h. Because of congestion in power networks, the electricity supply costs in different areas may also be different [49]. Hence, we assume heterogeneous electricity prices across the transportation network, i.e., 0.12 $/kWh at nodes 6-8, 11-13, 16; 0.20 $/kWh at nodes 10, 14, 21-25, and 0.30 $/kWh at other nodes.

For the base case, we assume the AEVs’ battery capacities are all 75 kWh, which is equal to that of a TESLA Model 3. However, we will not model the network driving constraints of the AEVs described in Section II based on this value because of four major reasons: 1) First, an AEV should conserve sufficient residual battery electricity to make sure that it can reach to the next charging station safely; 2) Second, a battery’s charging speed will dramatically slow down when its state-of-charge gets high so that an AEV will not tend to get fully charged to save time; 3) Thirdly, the fuel efficiency of an AEV may change with traffic or environmental conditions; and 4) Lastly, the battery capacity of an AEV may degrade during the lifetime. Therefore, we only use 60 kWh battery capacity to calculate the driving range of AEVs in the transportation network. For other scenarios with different battery capacities, we also deduct 15 kWh from the nameplate capacity to calculate driving range because of the aforementioned reasons.15

The expanded transportation network has 25 nodes with 590 arcs and $25 \times 24 = 600$ OD pairs. The scales of major decision variables $\lambda^{path}$ and $\lambda^r$ are both in the magnitude of 8 million. We first substitute them by $\lambda^{path}$ and $\lambda^r$, using equations (10)–(11). Then, we set the maximum path number of one OD pair $k = 150$ and $gap = 10^{-4}$ and adopt the approaches in Section IV to eliminate the redundant paths. As a result, by eliminating redundant paths in Section IV-A, the scale of decision variables $\lambda^{path}$ is only in the magnitude of 0.1 million. By eliminating redundant paths in Section IV-B, the number of $\lambda^{path}$ is only $590 \times 24 = 14160$. In summary, by utilizing the proposed pre-processing approaches, the scale of decision variables is reduced by about 98%. The original problem is intractable, but the new problem with the proposed pre-processing approaches can be solved by Gurobi [54] on a desktop with a 36-core Intel Xeon Gold 6140 CPU and 64 GB memory in less than 30 minutes.16

B. Results and Analysis

We adopt three benchmarks to validate the efficacy of the proposed strategy, as follows: 1) MinTime: the AEVs simply choose their shortest paths (with minimum driving time) to drive; 2) MinOperation: the AEVs simply choose their minimum operation paths (with minimum operation costs) to drive; and 3) NoRelocation: the AEV fleet operator does not actively relocate the AEVs during the day; instead, it only relocates the AEVs to their initial states after one day of operation. The proposed strategy is based on the models summarized in Section III-C, i.e., P1 for passenger transportation and P2 for goods transportation, respectively.

The planning results for both passenger and goods transportation in the base cases are summarized in Table III. The allocations of chargers adopting the proposed strategy are shown in Fig. 4 for illustration. Generally, for the system with 15,000 trips/day, a total of 2,500+ AEVs and 300+ chargers

15Note that this parameter is for illustrative purpose only. In practice, the planner should choose an appropriate number based on the actual electricity consumption estimation and availability of charging services.

16This includes both the pre-processing time and the algorithm time. Because that the scale of the expanded network is small (the cardinality of its arc set is limited by $|I|^2$), generating it takes less than one minute.
Fig. 3. Planning results with different rated charging power. (a), sizes of the EV fleet and charging systems. (b), investment costs. (c), time costs (Note that there is no time costs for goods transportation), (d) electricity costs, (e) maintenance costs, (f) total costs.

As expected, the proposed strategy is the most beneficial one for both passenger and goods transportation. Compared with the MinTime, MinOperation and NoRelocation Strategies, the proposed strategy can significantly reduce the required investments, especially for chargers, by optimally routing AEVs and scheduling their charging locations. Though the total costs reduction may be marginal (because of high operation costs share), the proposed strategy can reduce investment costs by at least 4.4% and 8.8% compared with benchmarks for passenger and goods transportation, respectively. This can help the company to reduce high capital investment that can be vitally important when its budget is limited.

When adopting the MinTime strategy, AEVs tend to choose the paths that will minimize the total passenger time on the road. However, because it overlooks other operation costs, its electricity costs will be higher. This will deteriorate the optimization results for goods transportation when electricity is the dominant cost factor leading to an 8.1% increase of the total costs compared with the proposed strategy. However, its planning results are pretty close to the MinOperation strategy.

The performance of the MinOperation strategy is quite close to the proposed one. The operation costs for both of the two strategies are approximately equal. However, the latter does remarkably advance the former in terms of investment costs. This indicates that the proposed strategy can effectively coordinate the route choices of AEVs in different OD pairs (with heterogeneous driving behaviors) to reduce charging demand peaks without sacrificing operation costs too much.

Relocating AEVs during the operation is quite important for promoting AEV utilization and reduce system costs. Without actively relocating AEVs, the number of AEV fleet could be 26.6% and 26.4% higher for passenger and goods transportation, respectively. At the same time, the number of chargers could be doubled for both cases so that the investment costs can be 40.5% and 41.9% higher, respectively.

Generally, the proposed strategy is more effective for goods transportation with less operation costs share. With the same quantity of mobility demands, the investment and electricity costs for goods transportation are 5.1% and 12.7% lower than those of passenger transportation, respectively. That is because AEVs are more willing to detour when carrying goods than passengers. For the latter, the passenger time cost is the dominant cost factor so that detouring, which increase driving and charging time, will be expensive. However, for the former, there is no passenger time cost and electricity cost is the dominant factor that is comparatively cheaper. Hence, AEVs are more willing to detour to charge cheaper electricity and this also reduces investments for both fleet with chargers.

Fig. 4. Charging station planning results adopting the proposed strategy. The integers next to the nodes are number of chargers at each location.
C. Sensitivity Analysis

1) Rated Charging Power: As mentioned earlier, because charging is much slower than gas filling, it can lead to considerable downtime (up to 45 minutes or more). With the fast development of battery storage and power electronic technologies, the rated charging power of chargers will also increase. The planning results of the fleet size and charging system as well as the corresponding costs structure with different rated charging power are illustrated in Fig. 3.

When the power increases, a same charger can satisfy more demands and the average charging time of AEVs will be lowered. Thus, the demands for AEVs and chargers are both reduced remarkably. Though installing high-power chargers is quite expensive, the experiment results show that investing in higher power chargers is more economical.\textsuperscript{17}

2) Battery Capacity: Battery capacity is another factor that may significantly affect the system’s performance. The summary of the planning results with different battery capacities are illustrated in Fig. 5. When AEVs’ battery capacity rises up, their fuel efficiency will reduce due to added mass. As a result, AEVs’ electricity consumption will increase so that the demands for chargers and electricity costs will rise up. For goods transportation, this will increase the system’s total costs and not be economical.

However, for passenger transportation, AEVs with higher battery capacity will charge less often on road so that they can save passengers’ time costs. This cost reduction may counteract the cost increment due to higher electricity consumption. As is shown in Fig. 5(f), the total costs of the system for passenger transportation first decrease and then increase with the increase of battery capacity. The 60 kWh battery capacity leads to the lowest cost.

The simulation results also show that the battery capacity has negligible effect on fleet size. Based on our assumption [A3], we require that an AEV will get fully charged when it arrives at a destination before it can be scheduled for the next trip. Hence, an AEV usually gets charged for at least once during each trip so that for AEVs with different battery capacities, their electricity consumptions will also be

\textsuperscript{17}Note that, in these experiments, we did not count the possible demands for power system upgrades to support the chargers.
close because they have similar daily mileages traveled. As a result, they will spend similar time for charging given the same rated charging power. Thus, larger battery will not help reduce fleet size. Note that with the assumption [A3], we will make a conservative planning result so that the system can be more robust. For scenarios with average trips long enough that AEVs need to get charged for at least once during each trip, the optimization result will be close to the actual optimal value.

3) Average Driving Speed: For AEVs, it is possible that the mobility technology will relax the current transportation regulations, e.g., speed limit. As a result, AEVs may be allowed to drive with higher speed. However, AEVs’ fuel efficiency is quite sensitive to their driving speed, when the driving speed increases, the fuel efficiency decreases [55], [56]. For a Tesla Model S, when its driving speed increases by 10 km/hour, its driving range reduces by approximately 45 km [55]. We assume the AEVs’ fuel efficiency is close to a Tesla Model S. Then, we validate how driving speed may impact the planning results, which is summarized in Fig. 6. As expected, when the driving speed goes up, the electricity consumption and the demands for chargers increase. In contrary, the total driving time decreases. When we increase the speed of AEVs, the fleet size first reduces then increases. This is because when the speed is too high, AEVs will consume more electricity and spend more time charging on road, which will offset the saved driving time. For passenger transportation, there is an obvious trade-off between saving passenger time and saving electricity consumption in terms of driving speed. While for goods transportation, if the delivery time is not urgent, the AEVs may not tend to drive too fast.\(^{18}\)

VI. CONCLUSION

We propose a planning model to right-size an AEV fleet and charging stations at least cost while meeting transport demands for both passenger and goods transportation. Based on the proposed model we studied various parameters’ impact on the system performance. Numerical experiments prove that the proposed strategy can effectively balance the investment costs and operation costs of the AEV system. By considering future routing and relocating operations, we can remarkably reduce the investment costs at the planning stage. The planning results also show that AEVs tend to detour more for goods transportation compared with passenger transportation because detouring with passengers may lead to significant time costs.

Adopting higher power chargers will reduce the downtime of AEVs due to charging, so that the turn-over rate of chargers and the utilization of AEVs are enhanced. Thus, higher charging power results in a lower required number of chargers and AEV fleet size. However, in practice, the company may need to upgrade expensive power supply infrastructure in order to support high power chargers and AEV batteries may age faster using higher power chargers. This may cancel out the mentioned benefits, which needs further study.

Larger battery capacity leads to lower fuel efficiency (which means more electricity consumption) and less charging time with passengers on road. As a result, it is not reasonable to invest in larger AEV batteries for goods transportation because there is not passenger time cost. However, the battery capacity should be carefully designed for passenger transportation balancing fuel consumption increase and charging time reduction.

AEVs’ driving speed can also significantly impact the planning results. AEVs’ turnover rate and fuel efficiency are both sensitive to driving speed. For passenger transportation, there is an obvious trade-off between saving passenger time and saving electricity consumption in terms of driving speed. While for goods transportation, if the delivery time is not urgent, the AEVs may not tend to drive too fast.

In this paper, we assume that there is no time window constraint for goods transportation. However, in practice, this may not hold so that AEVs will not be able to detour too much, either. In that case, we may estimate how much an AEV can detour based on the time window constraints \textit{a priori} offline. Then, we can identify the set of paths that AEVs can actually take subject to the time window constraint. We also assume whenever an AEV arrives at its destination, it will get fully charged before driving to another location, which is a mild one for long-distance transportation. However, if the mobility demands are short-distance ones, i.e., taxi-hailing services in urban areas, this assumption will make our planning results conservative. Relaxing this constraint will be our future focus.

In practice, the AEVs may be heterogeneous. As a result, a fleet of AEVs may have different driving ranges. In that case, we can 1) generate one expanded transportation network for each type of AEVs, or 2) generate the expanded transportation network according to the minimum driving range. The former can effectively consider heterogeneous AEVs but will increase the computational efficiency of the problem. While though the latter will not increase the computational efficiency, it may lead to conservative planning results. We will also consider heterogeneous AEVs in our future work.

REFERENCES


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