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Autonomous Vehicle Intelligent System: Joint Ride-Sharing and Parcel Delivery Strategy

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***Abstract*— Autonomous vehicle (AV) integration poses a significant challenge for intelligent transportation systems (ITSs). The ability to automatically coordinate complex AV operations at scale is crucial for advancing the quality of core transportation services, such as ride-sharing and parcel delivery. However, existing studies have only considered either of these two services independently from the other, disregarding the potential benefits of their combined optimization. To address this open problem, we design an autonomous vehicle intelligent system (AVIS) providing joint ride-sharing and parcel delivery services under realistic ride and route constraints. We formulate the joint optimization problem through the scope of mixed-integer linear programming and solve it using the Lagrangian dual decomposition method to ensure scalability. We conduct extensive case studies to evaluate the performance of the proposed AVIS and its constituting components. Our experimental results demonstrate that AVIS can effectively provide both ride-sharing and parcel delivery services while satisfying service requests in transportation networks of various scales. In addition, the distributed method is shown to generate near-optimal solutions in reduced computation time.**

***Index Terms*— Autonomous vehicles, Lagrangian dual decomposition, intelligent transportation systems, parcel delivery, ride-sharing.**

I. INTRODUCTION

THE SMART city paradigm has emerged as a promising avenue towards enhancing the quality of life in urban areas. Powered by recent advances in data sensing, communication, and processing, smart cities are bound to transform a wide range of core transportation operations and services. Intelligent Transportation Systems (ITSs) aim to provide users with reliable and efficient transportation services while making optimal use of the underlying infrastructure [1]. Upgrading traditional transportation systems to ITSs requires the convergence of several technologies, key among which are autonomous vehicles (AVs) [2]–[4]. Combined with vehicle-to-everything (V2X) technology, smart sensors installed on AVs enable the exchange of individually sensed information in real-time [5], [6], thereby improving the vehicles' collective awareness of the surrounding environment. In addition, the centralized ITS control center can leverage such information to determine and remotely broadcast individual routing instructions so that AVs can achieve the desired ITS objectives [7], [8]. In this manner, the utilization of AVs will contribute not only to safer and more efficient transportation with reduced traffic congestion, but also to improving critical services such as ride-sharing and parcel delivery. The provision of these services contribute to the real application of multi-mode transportation systems in smart cities, which refer to the combination of at least two or more various vehicular modes. The use of multi-modal planning, which considers various modes and connections among modes, can effectively response many different demands rather than the conventional mode in ITS [9].

Ride-sharing refers to the provision of a single transportation service to multiple passengers with overlapping travel plans. Typically offered via smartphone applications of ride-hailing services such as Uber and Lyft [10], ride-sharing provides users with on-demand, convenient, and cost-effective transportation [11], [12]. By maximizing vehicle occupancy such that fewer vehicles are ultimately deployed, ride-sharing results in considerable energy savings while also encouraging social interactions [13]. Existing studies [14]–[20] have focused on path-planning for ride-sharing services, with methods such as genetic algorithms and deep reinforcement learning attaining promising results. However, these studies have not explored the use of AVs in logistics services.

AVs can also help optimize supply chain management by offering logistics services such as parcel delivery [21], [22]. With the ever-growing demand for parcel delivery, AVs have become a promising candidate due to their capacity for dynamic, cost-effective routing, in addition to their relatively large storage capacity. Several works have demonstrated the effectiveness of AV-supported logistics services in ITSs [23]–[26]. Although these studies have evaluated the feasibility of AV-provided parcel delivery, they have similarly

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neglected to investigate the additional provision of ride-sharing services.

To bridge the research gaps related to the current ride-sharing and parcel delivery schemes, we develop an autonomous vehicle intelligent system (AVIS) to jointly provide ride-sharing and parcel delivery services in an integrated manner. In particular, we focus on how to schedule both ride-sharing and parcel delivery services to satisfy service requests under well-defined constraints and in a cost-effective manner. The main contributions of this work can be summarized as follows:

- We design a generic AVIS to provide joint ride-sharing and parcel delivery services using AVs, which also guarantees the efficient path-planning operations. This model is more general and practical than the existing studies since the cost-effective approach is developed within the feasible regions.
- We formulate the joint provision of the above services via mixed-integer linear programming (MILP) in AVIS. This helps to understand how the system operator and AVs interact so as to achieve better system performance.
- We derive a distributed method based on Lagrangian dual decomposition to solve the formulated joint problem in a scalable manner. This presents the devised algorithm can achieve near-optimal performance.
- We evaluate the performance of the proposed AVIS through a comprehensive series of case studies. Through the proposed AVIS, the economical benefit and effectiveness of the entire system can be achieved.

The rest of this paper is organized as follows. Section II examines closely related studies and identifies the challenges that motivate this work. Section III then develops AVIS, a model encompassing transportation networks, AVs, and system operations. Section IV formulates the joint problem of ride-sharing and parcel delivery, while Section V derives the distributed method proposed to solve the target optimization problem in a scalable manner. Next, Section VI details the case studies conducted to evaluate AVIS, with Section VII concluding this work.

II. Related Work

AVs will play a crucial part in the success of future ITSs. But before their full potential can be realized, AVs must tackle fundamental issues such as real-time motion planning and safe interaction with human-driven vehicles [27]. In this direction, [28] introduced an online routing framework based on deep reinforcement learning to minimize travel time, while [29] modeled vehicle behaviors as stochastic Markov decision processes and similarly leveraged deep reinforcement learning to obtain optimal driving actions. In addition, [30] introduced several observation-based control strategies for path tracking, with [31] proposing a motion planning framework for autonomous driving that incorporates target motion prediction. Hence, these existing studies clearly presented the effectiveness of using AVs in ITS.

With the gradual trends of AV adoptions in urban areas, ride-sharing services are expected to significantly benefit from these vehicles [32], [33]. In this direction, [14] proposed an autonomous on-demand ride-pooling system that was shown to effectively reduce traffic on major roads. Reference [15] modeled an autonomous taxi system as two bipartite optimization problems with vehicle-to-user and relocation assignments. To tackle the problem of electric vehicle fleet dispatch, [16] introduced a framework leveraging decentralized deep reinforcement learning and centralized decision making via linear assignment. In addition, after formulating the routing problem as a Markov decision process, [17] sampled service requests according to historical data and applied deep reinforcement learning to determine the best route. By following a mixed integer linear formulation, [18] tackled admission control via bi-level optimization with scheduling constraints and solved it using a genetic algorithm. Besides, [19] developed a public vehicle system providing online ride-sharing services under limited AVs and operation costs, using a greedy algorithm for path-planning. Furthermore, [20] proposed an autonomous taxi dispatching system with support for dynamic trip and adjustment of AV capacity. All these works recommend that AVs with the provision of ride-sharing services can benefit the modern transportation system operation.

The integration of AVs in smart cities is also expected to improve the quality of logistics services. For instance, several works have studied AV-provided parcel delivery [23]–[26]. Aiming to improve service quality with fewer required vehicles, [23] developed a parcel delivery planning and control system in order to handle the increasing demands on transport logistics. Moreover, [24] proposed an algorithm for AVs to safely navigate and efficiently deliver parcels in large-scale urban areas. Aiming to minimize the total service duration under routing constraints, [25] proposed a dynamic AV routing model based on Markov decision processes and approximate dynamic programming. Besides, [26] simulated the use of private AVs for both passenger transport and parcel delivery at city-scale, with findings suggesting that such practice can considerably minimize operator costs. Nonetheless, the above studies have not addressed AV-provided ride-sharing services.

Considering the provision of ride-sharing services, [34] built a last-mile parcel delivery system to assign delivery tasks based on a landmark graph that estimates road-segment-level travel times and fuel consumption by means of private cars. [35] devised a dynamic planning scheme to handle online trip requests for electric taxis under charging constraints. In addition, [36] proposed sharing models to handle both passengers and parcels in an integrated way by means of the taxi network. However, these works only involve short-distance delivery and trip services of private cars or electric taxis; as such, they have not considered the utilization of general AVs towards improving system performance. In this work, we tackle the random assignments for providing the joint services by means of general AVs. Finally, recent work [37] proposed a distributed deep reinforcement learning method to jointly serve passengers and goods workloads via learning optimal dispatch policies. Despite being a promising step in the right direction, this work neglects the constraints related to urgent goods delivery and the cost-effectiveness of the system. In this work, we explicitly consider the implementation of all

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types of parcels with different deadlines, in order to bridge this research gap.

Beyond the aforementioned studies, [38] proposed an autonomous vehicle logistic system (AVLS) leveraging AVs for joint routing and charging. AVLS provides logistic services for smart cities while also determining optimal routes and charging schedules. Even though AVLS can effectively use AVs to provide joint routing and charging services, it cannot readily provide ride-sharing. In addition, the deadlines for ride and logistic service requests are unique, while the proposed riding scheme neither varies the number of passengers nor considers the capacities of general AVs. Thus, how to provide ride-sharing in AVLS remains an open problem. In this paper, inspired by AVLS, we design a generic AVIS that integrates the provision of ride-sharing and parcel delivery services for general AVs in smart cities.

III. AVIS Architecture

This section presents the architecture of the proposed AVIS, which models transportation networks, AVs, and system operations.

A. Transportation Network

We model the transportation network to represent the physical distance from one location to another within a particular area. For simplicity of representation, the transportation network is modeled as a directed graph $G(\mathcal{V}, \mathcal{E})$, where the set of nodes $\mathcal{V}$ denotes road segment intersection points connected by edges in the set $\mathcal{E}$. We further define $d_{ij,n}$ as the travel distance of AV n from location i to location j for every road segment $(i, j) \in \mathcal{E}$. Note that $d_{ij,n}$ may not always equal $d_{ji,n}$ due to possible asymmetries between routes.

B. Autonomous Vehicles

We denote the set of participating genereal AVs as $\mathcal{N}$ and consider both public and private AVs in our design. The public AVs refer to the vehicles for serving transportation systems, e.g. public buses. These vehicles mainly serve the city public services with pre-determined schedules. For private AVs, they are defined as the fleet of AVs owned by citizens. These vehicles have the randomness characteristics on travel behaviors since the travel plans of such vehicles are determined by personal preferences. The utilization of general AVs in the AVIS can include the case of using both public and private AVs for tackling random service requests. AVs complete their assigned ride-sharing or parcel delivery objectives by traveling between any two locations (i, j), where $i, j \in \mathcal{V}$. AVs are able to provide both ride-sharing and delivery services for a predetermined time period. Finally, each service request is assigned to the n-th AV and must be completed within service deadline T_n^{ddl}.

Besides, for logistic services provided by AVs, we denote the index set of parcels as $\mathcal{W}$. Then, we define the index set of passengers as $\mathcal{Z}$ for ride-sharing services. For multiple service requests, we denote the index set of joint service requests as $\mathcal{R}$, where $\mathcal{R}_p \cup \mathcal{R}_s = \mathcal{R}$ are the sets of parcel delivery and ride-sharing service requests, respectively.

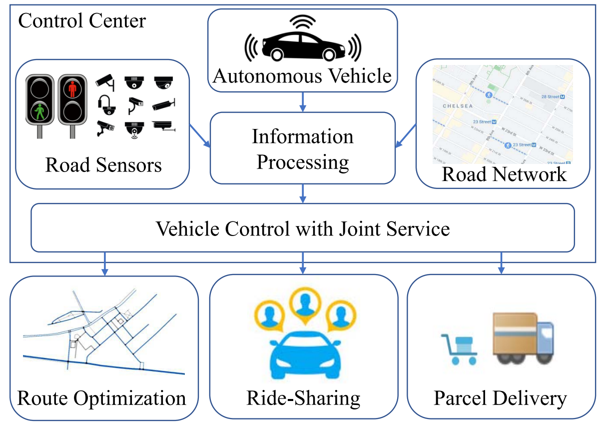

Fig. 1. Architecture of the proposed AVIS for joint ride-sharing and parcel delivery of autonomous vehicles.

C. System Operations

Following the public transportation system architecture in [18], our proposed AVIS incorporates a system control center to coordinate the optimal routing of AVs in the transportation network. An overview of the system architecture of AVIS is shown in Fig. 1. Note that routing is subject to ride-sharing and parcel delivery requirements, as described in Section III-A. Instead of the fixed assignment, we place the locations of all passengers and parcels into different areas using randomization for the random assignment. After processing traffic flow information from road sensors, AVs, as well as the transportation network, the control center performs route optimization for ride-sharing and parcel delivery.

The complete service process can be divided into two stages: planning and implementation. First, the control center determines the optimal route for each AV when receiving the city traffic and vehicular information. In the meantime, AVs are assumed to remain near the depot that has parcels in need for delivery. Next, the control center gathers the information of the transportation network, the current status of AVs, and existing logistic requests. At this time, the control center coordinates the ride-sharing services through the current capacity of AVs and the number of passengers within the participation time period. Then, it determines the routing, ride-sharing and parcel delivery plans for the AVs with the considerations of the logistic and ride-sharing requests. The real-time parameters are indeed utilized in the AV plans so as to tackle the stochastic traffic conditions. Finally, AVs proceed with the service plan for implementation. For the implementation stage, it is possible that traffic conditions may need to be updated in real-time. In such cases, the control center can re-assign AV service plans based on the new information. Once the congested traffic road segment $(i, j) \in \mathcal{E}$ occurs, the AV travel plans may be affected due to the constraints of service deadline.

A simplified example of joint ride-sharing and parcel delivery is depicted in Fig. 2. First, AV n departs from the initial location and approaches location 1 to load the parcels to be delivered. For the nodes serving on logistic services, the method for loading parcels follows [39]. Specifically, in [39], a decision support model is formulated as a mixed integer

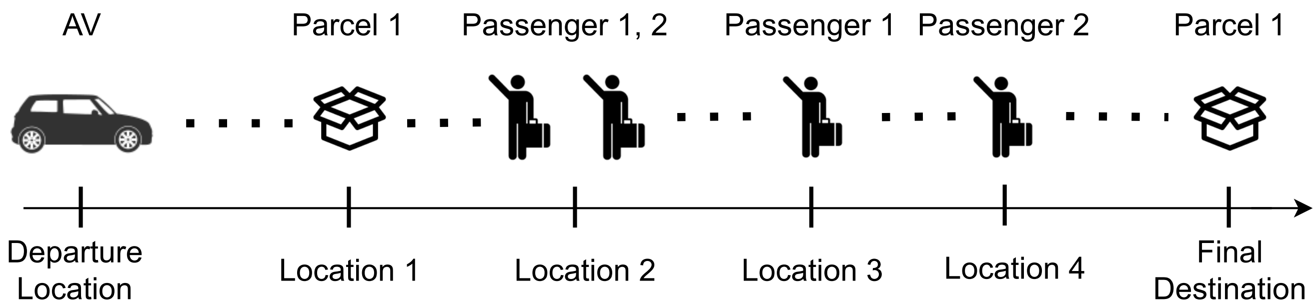

Fig. 2. A simplified process of joint ride-sharing and parcel delivery.

programming to achieve the total operational and logistics costs, which is used for assigning products and determining the paths of products flowing through the retail network. For ride-sharing service, AV n will reach location 2 and provide the ride-sharing service for the passengers 1 and 2 based on its available capacity. Next, these passengers will be taken to their predetermined destinations, i.e., locations 3 and 4. Finally, the AV reaches its final destination to complete the parcel delivery service before the service deadline. Please note that Fig. 2 presents a simplified way of providing the joint ride-sharing and parcel delivery service. In practice, it is possible that AV n will have to pick up more passengers and provide delivery services for a larger quantity of parcels during each request. Furthermore, in this work, we assume that the capacity for loading parcels of each AV is less than the capacity of the installed truck.

The control center in AVIS periodically requests information from each AV, the size of which depends on the scale of the modeled system. This is facilitated by communication technologies such as vehicular ad-hoc networks (VANETs), which enable wireless communication such that an internet of vehicles can ultimately be established [40], [41]. VANETs can facilitate both vehicle-to-roadside base station and inter-vehicle communications [38], requiring occasional connectivity to share positioning (and other) information. As previously mentioned, the planning and implementation stages consist of information gathering and execution of the provided routing plans by each AV, respectively. With the formation of VANETs, the time for data collection and service request assignment can be reduced to seconds.

IV. Problem Formulation

As discussed in Section III, the purpose of AVIS is to address the open problem of joint ride-sharing and parcel delivery for all participating AVs in a smart city. This section details our formulation of the above problem. All related parameters are disambiguated in Table I.

A. Operational Constraints

Let binary variable $x_{ij,n}$ denote whether AV $n \in \mathcal{N}$ traverses the road segment (i, j) as follows:

$$x_{ij,n} = \begin{cases} 1 & \text{if AV } n \text{ traverses road segment } (i, j) \in \mathcal{E}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

TABLE I
Table of Parameters for the Proposed AVIS

Parameters	
$\mathcal{V}$	Index set of nodes
N_V	Total number of nodes
$\mathcal{E}$	Index set of road paths
N_E	Total number of road paths
$\mathcal{N}$	Index set of AVs
N_{AV}	Total number of AVs
$\mathcal{W}$	Index set of parcels
$\mathcal{Z}$	Index set of passengers
$\mathcal{L}_n^{\text{dlv}}$	Set of delivery location of AV n
L_n^{src}	Departure point (source) of AV n
L_n^{dst}	Destination point of AV n
$T_{j,n}$	Stay time for AV n at location j
T_n^{ddl}	Service deadline of AV n
$H_n^{\max}$	Maximum loading capacity for AV n
$T_{ij,n}$	Travel time of AV n on road (i, j)
θ_{ij}	Delay factor for stochastic traffic over road (i, j)
$T_{n,r}^{\min}$	Minimum service time for AV n at request r
$T_{n,r}^{\max}$	Maximum service time for AV n at request r
$q_{i,n}$	Changing number of passengers of AV n at node j
Q_{ij}	Maximum volume of vehicles for road (i, j)
α_n	Unit routing cost of AV n
β_n	Unit transportation service cost of AV n
Optimization variables	
$x_{ij,n}$	Binary variable of whether AV n traverses road (i, j)
$d_{j,n}$	Staying duration of AV n at node j
$t_{j,n}$	Time of arrival of AV n at node j
$h_{j,n}$	Loading capacity for AV n at node j
$C_{j,n}$	Capacity of AV n at node j

In practice, AVs can visit the same node multiple times in the course of different trips. To simplify our problem formulation, we assume that each AV $n \in \mathcal{N}$ can visit each node of the transportation network at most once. We further define the status of AV n at node $j \in \mathcal{V}$. In particular, we denote $t_{j,n} \geq 0$ as the time when AV n arrives at node j. In addition, we define $d_{j,n} \geq 0$ as the duration of AV n staying at node j.

The proposed AVIS encompasses three main operations: AV routing, parcel delivery, and ride-sharing. Ensuring real-world applicability demands that all AV operations be performed while satisfying a set of specified constraints. The latter are presented in the sequel.

1) Route Constraints: In AVIS, the n-th AV shall reach its final destination after receiving a request assignment for a certain operation, i.e., ride-sharing or parcel delivery. This implies that the AV will have to traverse at least one road segment to reach the final destination. This can be ensured by:

$$\sum_{i\in\mathcal{V}} x_{ij,n} \geq 1,\ \forall n \in \mathcal{N},\ j \in \{\mathcal{L}_n^{\text{dlv}}\}, \tag{2}$$

where $\mathcal{L}_n^{\text{dlv}}$ denotes the set of delivery location of AV n.

We model the AV network flow model based on the city's road network. We define $\sum_{i\in\mathcal{V}} x_{ij,n}$ and $\sum_{i\in\mathcal{V}} x_{ji,n}$ as the incoming and outgoing flows, respectively. The connectivity of multiple consecutive road segments for AV $n \in \mathcal{N}$ can be guaranteed by:

$$\sum_{i\in\mathcal{V}} x_{ij,n} - \sum_{i\in\mathcal{V}} x_{ji,n} = \begin{cases} 1 & \text{if } j = L_n^{\text{dst}}, L_n^{\text{src}} \neq L_n^{\text{dst}}, \\ -1 & \text{if } j = L_n^{\text{src}}, L_n^{\text{src}} \neq L_n^{\text{dst}}, \\ 0 & \text{otherwise}, \end{cases} \tag{3}$$

where L_n^{src} and L_n^{dst} represent the departure and destination points of the corresponding routes of AV n. In (3), the first two cases ensure that if AV n approaches node j, there shall be an incoming flow and outgoing flow between the departure and destination points, respectively. For example, considering all road interactions other than those involving the departure and destination points, if AV n approaches node j, an incoming flow will lead to an outgoing one. Otherwise, the number of incoming and outgoing flows for AVs will be the same. Thus, (3) guarantees the connectivity of vehicular routes. In practice, it is possible to consider the utilization of different types of vehicles in smart cities. Hence, when considering the utilization of the public vehicles, e.g. city buses, the constraints (1) - (3) shall be neglected, since the routes have already been determined by the public transportation system.

In practice, access to some roads may be restricted for certain vehicles. For instance, private cars are often not allowed to travel on road segments for authorized vehicles. To take such realistic scenarios into consideration, we can model additional constraints. We first define $(\mathcal{V}', \mathcal{E}')$, where the set of nodes $\mathcal{V}' \subset \mathcal{V}$ denotes road segment intersection points connected by edges in the set $\mathcal{E}' \subset \mathcal{E}$ in the restricted zone. Suppose that access to road (i, j) is restricted for AV n. The related constraint can be modeled as $x_{ij,n} = 0,\ \forall i \in \mathcal{V}',\ j \in \mathcal{E}'$, which means that there is AV n is not allowed to travel between node i and node j since it is within a restricted zone.

2) Parcel Delivery Constraints: Parcel delivery needs to consider the quality of the provided services. In this context, we measure quality of service as the time required for delivery. When the n-th AV n loads or unloads parcels at node j, the minimum duration of stay is denoted by:

$$d_{j,n} \geq T_{j,n},\ \forall n \in \mathcal{N},\ j \in \mathcal{V}, r \in \mathcal{R}_p, \tag{4}$$

where $T_{j,n}$ is the stay time for loading or unloading parcels for the n-th AV.

In addition, recall that $t_{j,n}$ represents the time when the n-th AV arrives at node j. For accuracy of estimation, we also need to account for the time of AV n traversing the involved the nodes and road segments of the traffic network, which refers to the time access windows in [42]. Note that, $t_{j,n}$ is updated when AV n complete all requests in the set of $\mathcal{R}_p$. When AV n travels through $(i, j) \in \mathcal{E}\backslash\{\mathcal{E}'\}$, $t_{j,n}$ will be no less than the time required for traveling plus the time for loading the parcels, which is defined by:

$$t_{j,n} \geq t_{i,n} + d_{i,n} + T_{ij,n},\ \forall x_{ij,n} = 1, n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{5}$$

where $T_{ij,n}$ denotes the travel time from node i to node j for the n-th AV. Since the stochastic traffic conditions may vary this parameter, we define the time-varying delay parameter θ_{ij} to indicate whether the sudden traffic congestion occurred over the road segment (i, j) or not, which can incur the degradation performance on $T_{ij,n}$. Specifically, it follows that $T_{ij,n}^{\text{real}} = T_{ij,n} + \theta_{ij}$, where $T_{ij,n}^{\text{real}}$ is the real-time travel time of AV n over the road (i, j) and it affects the quality of the provision of parcel delivery service due to the change in constraint (5). Moreover, θ_{ij} is updated in a real-time manner, since it is related to the real-time traffic condition over the road $(i, j) \in \mathcal{E}$. Then, its parcels will be delivered to the destination point according to:

$$T_{n,r}^{\min} \leq t_{j,n} \leq T_{n,r}^{\max},\ \forall n \in \mathcal{N}, j \in \mathcal{V}, r \in \mathcal{R}_p, \tag{6}$$

where $T_{n,r}^{\min}$ and $T_{n,r}^{\max}$ are the expected minimum and maximum times at the logistic service request r. Finally, the service deadline is the time required to complete the service at node L_n^{dst}, which follows:

$$t_{L_{\text{dst}}^n,n} \leq T_n^{\text{ddl}},\ \forall n \in \mathcal{N}, j \in \mathcal{V}, \tag{7}$$

where T_n^{ddl} denotes the service deadline for the n-th AV.

Besides time constraints, the loading capacity of parcel $w \in \mathcal{W}$ is defined to take into account during logistic services. We define $h_{j,n}$ as the loading capacity of AV n at node j, and it is updated when AV n complete each request $r \in \mathcal{R}_p$. Then, it follows:

$$h_{j,n} \leq H_n^{\max},\ \forall x_{ij,n} = 1, n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{8}$$

where $H_n^{\max}$ denotes the maximum loading capacity of AV n.

Considering the presence of restricted roads, we set the visiting time of AV n to zero. This means that AV n cannot visit node i based on (5). For the case of AV n being only allowed to travel at node j in a specific time period, we include the operational limits as (6).

3) Ride-Sharing Constraints: Our ride-sharing scheme accounts for the riding time of each passenger and the capacity of each AV. For each ride-sharing service request, the passengers should arrive at their destinations within the expected earliest and latest pickup or drop-off times, which is described by:

$$T_{n,r}^{\min} \leq t_{j,n} \leq T_{n,r}^{\max},\ \forall n \in \mathcal{N}, j \in \mathcal{V}, r \in \mathcal{R}_s. \tag{9}$$

Apart from time constraints, the capacity of AV n is defined to take into account the number of passengers it can hold during ride-sharing. We define $C_{j,n}$ as the capacity of AV n at node j. When AV n provides ride-sharing services through $(i, j) \in \mathcal{E}$, the residual capacity at node j shall be greater than the capacity at node i. This can be ensured by:

$$C_{j,n} \geq C_{i,n} + q_{i,n},\ \forall x_{ij,n} = 1, n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{10}$$

where $q_{i,n}$ denotes the loading number of passengers at node i for a ride involving the n-th AV. Moreover, $C_{j,n}$ is updated when AV n complete the request $r \in \mathcal{R}_s$.

To encourage the provision of the ride-sharing service, the number of AVs in every road segment is bounded by a maximum capacity. This can be expressed as:

$$\sum_{n\in\mathcal{N}} x_{ij,n} \leq Q_{ij}, \ \forall n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{11}$$

where Q_{ij} represents the maximum number of vehicles for road segment $(i, j) \in \mathcal{E}$.

Before the problem formulation of the proposed joint model, we assume that for both ride-sharing and parcel delivery services, the pickup/drop-off or loading/unloading nodes are set within the access zones so that we do not consider the services provided in the restricted zones. The related studies have adopted the assumption frequently, see [28], [38] as examples.

B. Objective Functions

AVIS delivers joint ride-sharing and parcel delivery taking into consideration two main system operation costs: total distance and delivery time.

The AV routing scheme is closely related to the total travel distance of each AV for every service request [38]. The operation cost related to the travel distance is described by:

$$F^{\text{route}} = \sum_{n\in\mathcal{N},(i,j)\in\mathcal{E}} \alpha_n d_{ij,n} x_{ij,n}, \tag{12}$$

where α_n denotes the unit routing cost for AV n and $d_{ij,n}$ is the travel distance of AV n from location i to location j for every road segment $(i, j) \in \mathcal{E}$.

On the other hand, the proposed scheme involves the operation cost for the service of delivering parcels. This service ensures that parcels are delivered as early as possible. Moreover, ride-sharing must guarantee customer satisfaction. Based on these aspects, the resulting cost function is:

$$F^{\text{service}} = \sum_{n\in\mathcal{N}} \beta_n t_{L_n^{\text{dst}},n}, \tag{13}$$

where β_n is the unit transportation service cost of AV n.

The control objective of AVIS is to minimize the total system operation costs related to AV routing and the service schemes described above. Hence, the joint ride-sharing and parcel delivery problem can be formulated as follows:

$$\text{minimize} \ \ F^{\text{total}} = F^{\text{route}} + F^{\text{service}}, \tag{14a}$$

$$\text{subject to} \ (2) - (11). \tag{14b}$$

C. Linear Transformation

Based on the previously formulated problem, it is evident that the objective function and most constraints are affine. Hence, these optimization problems can be handled with relative ease. However, constraints (5), (8), and (10) are modeled under the condition $x_{ij,n} = 1$. Without prior information on $x_{ij,n}$, these two constraints cannot be modeled directly. To tackle this issue, we aim to transform (5) and (10) to their equivalent linear forms. Before doing so, we consider the following two cases:

- Case 1: If $x_{ij,n} = 0$, AV n will not visit node j starting from node i through $(i, j) \in \mathcal{E}$. Hence, there is no relation between $t_{i,n}$ and $t_{j,n}$ because $t_{j,n}$ is confined within a feasible region. Similarly, there is no direct relation between $C_{i,n}$ and $C_{j,n}$.
- Case 2: If $x_{ij,n} = 1$, $t_{j,n}$ and $C_{j,n}$ must be greater than the right hand side of constraints (5) and (10).

We then transform constraints (5) and (10) into their linear forms as follows:

$$t_{j,n} \geq t_{i,n} + d_{i,n} + T_{ij,n} - M(1 - x_{ij,n}), \ \forall n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{15}$$

$$C_{j,n} \geq C_{i,n} + q_{i,n} - M(1 - x_{ij,n}), \ \forall n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{16}$$

where M is a sufficiently large number to ensure the feasibility of the constraints. In addition, since $T_{ij,n}^{\text{real}}$ affects constraint (15), the objective function shall be influenced due to the change of variable $t_{j,n}$.

In the meantime, we follow the same way to transform (8) into its linear form as:

$$h_{j,n} \leq H_n^{\max} - M(1 - x_{ij,n}), \ \forall n \in \mathcal{N}, i, j \in \mathcal{V}, \tag{17}$$

With the above simplifications, the proposed joint ride-sharing and parcel delivery can be re-formulated as:

$$\text{minimize} \ \ F^{\text{total}}, \tag{18a}$$

$$\text{subject to} \ (2) - (4), (6), (7), (11), (15), (16), (17). \tag{18b}$$

V. Distributed AVIS Optimization

The joint problem formulation in (18) is a mixed-integer linear programming (MILP) problem. As the number of AVs in the system increases, the computation time of this problem would grow dramatically since it would be solved in a centralized manner. Hence, a scalable method to solve this problem is required for real-world applications. By following [43], the formulated problem in (18) can be decomposed into the sub-problem of each AV, which make the problem easier be solved. Therefore, we devise a distributed algorithm via the Lagrangian dual decomposition method.

Based on (18), we introduce a Lagrangian multiplier $\lambda_{i,j} \geq 0$. It is evident that all constraints are separable with $n \in \mathcal{N}$, except for (11). To relax this constraint, the partial Lagrangian is developed as follows:

$$\begin{aligned}
&\sum_{n\in\mathcal{N},(i,j)\in\mathcal{E}} \alpha_n d_{ij,n} x_{ij,n} + \sum_{n\in\mathcal{N}} \beta_n t_{L_n^{\text{dst}},n} \\
&\quad + \sum_{n\in\mathcal{N}} \lambda_{i,j}(x_{ij,n} - Q_{ij}) \\
&= \sum_{n\in\mathcal{N}} \Bigg(\sum_{(i,j)\in\mathcal{E}} (\alpha_n d_{ij,n} x_{ij,n}) + \lambda_{i,j} x_{ij,n} \\
&\quad + \beta_n t_{L_n^{\text{dst}},n} \Bigg) - \lambda_{i,j} Q_{ij}.
\end{aligned} \tag{19}$$

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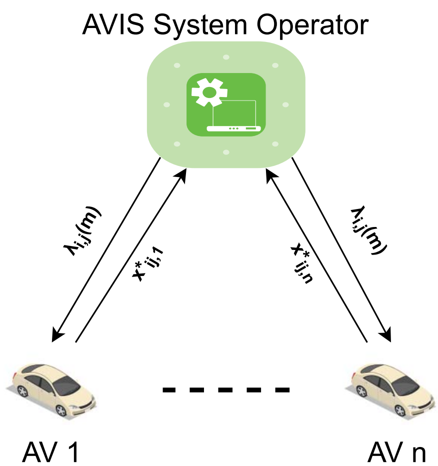

Fig. 3. Structure of distributed solution.

Given the above derivations, the dual function can be defined as:

$$g(\boldsymbol{\lambda}) = \sum_{n\in\mathcal{N}} \inf\Bigg\{ \sum_{(i,j)\in\mathcal{E}} (\alpha_n d_{ij,n} x_{ij,n}) + \lambda_{i,j} x_{ij,n} + \beta_n t_{L_n^{\text{dst}},n} \Bigg\} - \lambda_{i,j} Q_{ij}, \tag{20}$$

where $\boldsymbol{\lambda}$ is the set of Lagrangian multipliers and $\inf\{\cdot\}$ represents the infinite of the enclosed function.

It is important to establish that the dual function in (20) is convex. According to [44], the infimum of affine functions of $\boldsymbol{\lambda}$ is convex. Therefore, the dual function in (20) is also convex.

We can then formulate the sub-problem for the n-th AV in the system by decoupling the main problem as follows:

$$\text{minimize } G_n(\boldsymbol{\lambda}) = \sum_{(i,j)\in\mathcal{E}} (\alpha_n d_{ij,n} x_{ij,n}) + \lambda_{i,j} x_{ij,n} + \beta_n t_{L_n^{\text{dst}},n}, \tag{21a}$$

$$\text{subject to } (2) -- (4), (6), (7), (15), (16), (17). \tag{21b}$$

In turn, we formalize the dual problem as:

$$\text{minimize } G_n^*(\boldsymbol{\lambda}) - \lambda_{i,j} Q_{ij}, \tag{22a}$$

$$\text{subject to } \boldsymbol{\lambda} \geq 0, \tag{22b}$$

where $G_n^*(\boldsymbol{\lambda})$ represents the optimal solution of (21).

The optimal solutions for (22) can be utilized to recover the solution in primary problem (18). To solve (22) in an efficient manner, we leverage the projected gradient decent method to approximate the sub-optimal solutions instead [45]. This process is illustrated in Fig. 3. First, the AVIS operator broadcasts initial information to all participating AVs, such as city traffic networks and service requests. In each iteration, each AV then solves its own sub-problem following (21). When given G_n^* by solving (21), (22) can be effectively solved with the projected gradient descent method, which is an iterative method to effectively solve the dual problem. This method can minimize the objective function by moving a candidate solution in the gradient direction of the function $\frac{g(\boldsymbol{\lambda})}{\lambda_{i,j}}$, shown as:

$$\frac{g(\boldsymbol{\lambda})}{\lambda_{i,j}} = \sum_{n\in\mathcal{N}} x_{ij,n} - Q_{ij}. \tag{23}$$

Next, the sub-optimal solutions are transmitted to the AVIS operator who updates the Lagrangian multiplier accordingly. The update rules for Lagrangian multiplier can be written as follows:

$$\begin{aligned} \lambda_{i,j}(m+1) &= [\lambda_{i,j}(m) - \gamma_{i,j} \frac{\partial g_i(\boldsymbol{\lambda})}{\partial \lambda_{i,j}}]_+ \\ &= [\lambda_{i,j}(m) - \gamma_{i,j}(\sum_{i\in\mathcal{N}} x^*_{ij,n} - Q_{ij})]_+, \end{aligned} \tag{24}$$

where $[\cdot]_+$ refers to the $\max(0, \cdot)$ operator and $\gamma_{i,j}$ is the projected gradient descent step size. If we have $\sum_{i\in\mathcal{N}} x^*_{ij,n} \geq Q_{ij}$, it will violate (11). (24) can ensure that $\lambda_{i,j}(m+1)$ is greater than $\lambda_{i,j}(m)$, leading to small values of $x^*_{ij,n}(m+1)$ for the next iteration.

Algorithm 1 Joint Ride-Sharing and Parcel Delivery

```
Initialize λ_{i,j}
for m = 1: N_M do
  for each AV n ∈ 𝒩 do
    Solve (21) to obtain x*_{ij,n}(m)
    if δ < 10^{-4} then
      Return the optimal solution as x*_{ij,n}
    else
      m = m + 1
      Update λ_{i,j} using (24)
    end if
  end for
end for
```

We devise Algorithm 1 to solve each sub-problem in a distributed fashion. Using the projected gradient descent method, we obtain the sequence $\{\lambda_{i,j}(m), \forall m = 1, \ldots, N_m\}$. In the first step of the m-th iteration, the AVIS system operator broadcasts $\lambda_{i,j}(m)$ to all participating AVs. In the second step, the n-th AV solves each sub-problem (21) to obtain $x^*_{ij,n}(m)$. Each AV then returns the optimal solution to the AVIS system operator in the third step. Finally, the system operator determines the optimal decision by evaluating the stopping criterion, which determines the convergence of this algorithm:

$$\frac{|\sum_{n\in\mathcal{N}} g(m+1) - \sum_{n\in\mathcal{N}} g(m)|}{|\sum_{n\in\mathcal{N}} g(m+1)|} < \delta, \tag{25}$$

where $\delta = 10^{-4}$.

The primal solution of the original problem (18) can be recovered from the solutions to the sub-problems of AVs in a collective manner. The simple combination of the solutions from all sub-problems may have a solution that violates (11). Hence, we need to identify all combination of $g \in \mathcal{G}$ that violate the constraint (11). For each assignment, all vehicles operate at g are sorted by their service assignments. Then, since $x_{ij,n}$ is the binary variable to indicate whether AV n traverses the road segment (i, j) or not, we ensure the value of $x_{ij,n}$ such that the sufficient number of AVs are participating

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the provision of joint ride-sharing and parcel delivery service. This process repeats until (11) is satisfied, i.e. $\sum_{i \in \mathcal{N}} x^*_{ij,n} \leq Q_{ij}$. A feasible primal solution can then be constructed as the final solution to (18).

We note that the proposed distributed method only incurs minimal information exchange between the control center and the participating AVs. Rather than report all decision variables, the n-th AV only transmits the value of $x^*_{ij,n}$ to the control center on every iteration of Algorithm 1. This design choice aims to avoid the transmission of a large amount of redundant traffic information and vehicular data, given the sufficient number of participating AVs in the system. In addition, the proposed distributed approach can significantly minimize computation time significantly, as will be presented in Section VI.

VI. Case Studies

In this section, we assess the performance of the proposed AVIS. After detailing our experimental setup, we simulate three characteristic scenarios and evaluate the proposed system's quality of service within real-world transportation systems. Next, we investigate the impact of different AV fleet sizes and their effect on our evaluation metrics under realistic traffic network states. Finally, we examine the convergence of the distributed method.

A. Simulation Setup

To demonstrate the real-world applicability of the proposed AVIS, we evaluate its performance in real-world transportation systems. Specifically, our simulations are mainly conducted on the town of Carolina, Alabama; the corresponding traffic map is obtained from a public source. [1] In the captured area, there are a total of 26 nodes and 56 edges with different lengths. The minimum and maximum edge lengths are 18 meters (59 feet) and 725 meters (2379 feet), respectively. The number of AVs in Carolina is set to 50. To determine the average speed of the transportation network, we employ the vehicular mobility traces provided in [46]. Each AV is therefore set to travel with a constant speed of 112 kilometers (70 miles) per hour. According to [47], the transport costs α_n and β_n are set to \$1.73 per mile and \$83.68 per hour, respectively. We assume that there is no traffic congestion occurred on the traffic networks. For every service request, the final destinations of both ride-sharing and parcel delivery are randomly selected such that they are different from their departure positions.

Our parameter settings for the ride-sharing and parcel delivery services are as follows. For the former service, the number of passengers is set to 10, while the number of parcels for the latter service is set to 5. In addition, the maximum number of AVs for each edge is set to 4 in order to encourage the provision of ride-sharing services. For each AV, the deadline of arriving at the final destination to complete the joint service is set to 200 minutes. Regarding the parcel delivery service, the service time for loading and unloading parcels follows U[5, 30] minutes, while the deadline for all service requests are varied between 30 to 200 minutes. For the ride-sharing service, the minimum and maximum pickup/drop-off times for each passenger are varied between 30 and 90 minutes. The step size $\gamma_{i,j}$ of the distributed method is set to 0.01. According to the average latency of practical cellular systems [38], the one-way communication delay is assumed to be 100 milliseconds. Our simulations are conducted using MATLAB Release 2017a with the `mosek` optimization solver found in the `yalmip` toolbox.

As a final remark, we consider the priority of service requests to be linked with the associated service deadlines. In real-world systems, it is often the case that some service requests have higher priority than others. Thus, the distributed optimization method determines service order according to the condition of the associated transportation system.

TABLE II
Comparison of Different Scenarios in Carolina

Scenarios	S1	S2	S3	S1-C
Average unit cost (US$)	2593.1	2597.5	2608.4	3445.3
Average service time (min)	73.2	71.4	71.6	98.7

TABLE III
Comparison of Different Scenarios in Dodge City

Scenarios	S1	S2	S3	S1-C
Average unit cost (US$)	5821.2	6371.9	6442.1	8916.6
Average service time (min)	70.0	68.9	69.7	96.5

TABLE IV
Comparison of Different Scenarios in Garden City

Scenarios	S1	S2	S3	S1-C
Average unit cost (US$)	11872.0	10418.4	10639.9	14706.0
Average service time (min)	80.0	70.2	71.7	99.1

B. Quality of Joint Service

This simulation mainly studies the practicality of the proposed AVIS on the real traffic network of Carolina. The relevant directed graph is generated based on the dataset employed. To measure the efficacy of the joint service provided by AVIS, we simulate the following three scenarios: joint ride-sharing and parcel delivery (S1), ride-sharing only (S2), and parcel delivery only (S3). For S2, it only deals with the ride-sharing operations with the related constraints, while S3 only tackles the problem related to the provision of logistic services in urban areas.

Based on the configuration in Section VI-A, we first study the social welfare of the system under these three different scenarios, especially the unit operation cost per AV. Here, we use the metric of average unit cost to represent the mean expense across the joint service for each AV n. Table II shows that S1 obtains the lowest average unit operation cost and S2 obtain the lowest average service time. By providing multiple services simultaneously, the average unit operation cost of S1

[1] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/CUWWYJ

TABLE V
IMPACT OF DIFFERENT FLEET SIZE OF AVs

Number of AVs	10	20	50	100	200	300
Optimality gap (%)	0.83	0.75	0.68	0.64	0.48	0.34
Centralized time (min)	5.98	17.95	89.73	478.43	2152.93	6458.80
Distributed time (min)	0.65	1.31	3.26	6.52	13.04	19.57
Speedup ratio	9.17	13.76	27.51	73.36	165.06	330.12
Total cost (US$)	2.57×10^4	5.43×10^4	1.30×10^5	2.59×10^5	5.16×10^5	7.78×10^5
Average service time (min)	70.7	74.6	71.2	71.1	70.8	73.1

TABLE VI
OPTIMALITY AND COMPUTATION TIMES FOR DIFFERENT NUMBERS OF NODES WITH 50 AVs

Node number	N_V = 26	N_V = 66	N_V = 106
Obj: minimize the cost on travel distance.			
Optimality gap (%)	0.40	0.49	0.35
Centralized time (min)	196.76	4094.70	8127.10
Distributed time (min)	5.49	25.66	64.23
Obj: minimize the cost on service time.			
Optimality gap (%)	0.73	0.69	0.47
Centralized time (min)	203.33	3996.40	7452.70
Distributed time (min)	4.63	19.53	177.57
Obj: minimize the cost on travel distance and service time.			
Optimality gap (%)	0.68	0.63	0.50
Centralized time (min)	89.73	2172.30	4105.20
Distributed time (min)	3.26	53.09	573.95

TABLE VII
IMPACT OF VARYING TRANSPORTATION NETWORK SIZES WITH 50 AVs UNDER MULTIPLE SERVICE REQUESTS

City	Carolina	Dodge City	Garden City
(N_V, N_E)	(26, 56)	(66, 133)	(106, 268)
Optimality gap (%)	0.68	0.63	0.50
Centralized time (min)	89.73	2172.33	41052.41
Distributed time (min)	3.26	53.09	573.95
Speedup ratio	27.51	41.27	71.53

is lower than the summation expenses of S2 and S3. For the average service time, we generate 50 random problem cases for the requests by crossing over $\frac{1}{2}N_E$. In Table II, the time consumed for providing joint service under each request for S1 is much less than the total service time of S2 and S3. This indicates that S1 results in effective joint service provision by considering both ride-sharing and parcel delivery. Furthermore, we study the service quality under different traffic conditions. Here we denote S1-C as the one with traffic congestion conditions. Meanwhile, we set the delay parameter θ_{ij} to $\frac{1}{2}T_{ij,n}$ to indicate that the real-time travel time of AV n is increased due to the occurrence of traffic congestion over the road segment (i, j). According to Table II, we can observe that both the average unit cost and service time increase due to the AV routing operations over the congested traffic networks.

Next, we investigate the benefits of deploying the joint service in two other cities in Alabama: Dodge City ($N_V = 66, N_E = 133$) and Garden City ($N_V = 106, N_E = 268$). These two cities were selected because they have more complex network topologies than Carolina. Our experimental results, shown in Tables III and IV, indicate higher average unit operational costs with the increase of the network size through S1. This can be attributed to the increased complexity of the corresponding transportation networks, which raises the cost of scheduling AVs for services. Regarding average service time, we also produce 50 random cases with $N_{AV} = 50$. Even though providing the joint service in S1 requires somewhat higher average unit operational costs, we observe relatively low time consumption. Furthermore, by observing the results in Tables II, III, and IV, the increment of the network size increases the unit cost but may reduce the average service time. The reason is that the system operation is more flexible when increasing the network size. Therefore, S1 is capable of efficient joint ride-sharing and parcel delivery for different cities. Last but not least, we investigate the service quality under different traffic conditions in these two cities. According to Tables III and IV, we can observe that the AV routing operations over the congested traffic networks of these two cities indeed increase both the unit cost and service time in a sharp manner. The reason is that the system operation requires more cost and time when considering the congested road networks.

C. Impact of Fleet Size

Here we investigate the effect of fleet size on the performance of AVIS. We consider six different cases with 10, 20, 50, 100, 200, and 300 AVs, respectively. There are four performance metrics being tested, shown in Table V. Since the centralized method generates the best solution due to the existence of global optimal solution by solving (18) via the solver, we report the optimality gap of the distributed method relative to that of the centralized method as $(1-\frac{F_{\text{total}}^{\text{dist}}}{F_{\text{total}}^{\text{cent}}}) \times 100\%$, where $F_{\text{total}}^{\text{dist}}$ and $F_{\text{total}}^{\text{cent}}$ are the (sub-)optimal and optimal solutions for these two methods, respectively. According to our results in Table V, small gaps between the centralized and distributed solutions indicates that the optimality of the distributed solution exceeds 99%. Moreover, increasing fleet sizes improve the optimality of the distributed solution. The main reason is related to the system flexibility granted by higher numbers of participating AVs, which can further contribute to a better solution.

In addition, we study the computational complexity of the distributed method under the six different cases. By focusing on the computation time, Table V shows that the distributed method achieves much lower computation time than the

TABLE VIII
IMPACT OF VARYING TRANSPORTATION NETWORK SIZES WITH 50 AVS UNDER MULTIPLE SERVICE REQUESTS IN DIFFERENT CITIES

Carolina	Service Requests				
	1	2	3	4	5
Centralized time (min)	89.73	111.25	131.67	155.25	185.42
Distributed time (min)	3.26	3.75	4.07	4.37	4.88
Speedup ratio	27.51	29.63	32.35	35.53	37.99
Dodge City	**Service Requests**				
	1	2	3	4	5
Centralized time (min)	2172.33	2690.60	3015.39	3415.23	3706.57
Distributed time (min)	53.09	62.41	76.36	85.20	93.52
Speedup ratio	41.27	43.11	39.48	40.08	39.63
Garden City	**Service Requests**				
	1	2	3	4	5
Centralized time (min)	41052.41	47804.10	54776.39	58202.41	65209.62
Distributed time (min)	573.95	607.64	630.68	672.75	710.74
Speedup ratio	71.53	78.67	86.85	86.51	91.75

centralized method. The reason is that the utilization of the centralized method increases the computational complexity of the joint problem since the problem size is in proportion to the number of AVs. This indicates that more AVs in the system lead to more operational constraints to the optimization problem. In addition, for the distributed method, the problem size is unrelated to the fleet size, which leads to steady computational time. By observing the speedup ratio, the efficiency of the proposed distributed method in AVIS is presented when increasing the fleet sizes of AVs. Even though the distributed time increases in a relatively small scale, the complex problem with 300 AVs can be solved in an effective manner. Last but not least, by observing the last two rows of this table, the total system operational cost raises with the number of AVs increases. Nevertheless, when the number of AVs reaches 300, the average service time is relatively low. It clearly reflects the effectiveness of the proposed AVIS under different fleet of AVs.

D. Impact of Network Size

Apart from the fleet size, we further study the effect of network size on the proposed AVIS framework. Except for Carolina ($N_V = 26, N_E = 56$), we further investigate the performance of AVIS in Dodge city and Garden city. We utilize similar evaluation metrics as those in Section VI-C for this investigation. Our results are presented in Table VII. The optimality gap of the distributed solution is less than 1% with fairly high relative optimality for all three cities. It appears that, when traffic network sizes increase, so do computational complexity and computation time. This is not surprising, as more complex transportation networks are bound to result in more constraints to the formulated problem. Similarly, the distributed method reduces the complexity of the problem in all three evaluated cities, as reflected by the attained speedup ratio.

Next, we investigate the effectiveness of our objective function on the three traffic networks, measured by the minimization of either travel distance, service time, or both. Our results are presented in Table VI. We observe that there is no significant relationship between the objective function and the traffic network size. This can be attributed to the fact that the same physical driving distance between two locations in different cities does not affect the optimality of the devised algorithm. We note that the optimality of the distributed algorithm fluctuates due to the randomness of the different traffic networks. Meanwhile, computation time for all the three cases increases with more nodes considered in the traffic networks. The reason is that more traffic nodes introduce more operational constraints to the formulated problem, which further increase the computational complexity of the problem.

E. Investigation of Multiple Service Requests

In Table VIII, we evaluate the effect of every single service request offered in the proposed system under different city scales. In practice, there may be multiple service requests for each AV operating from the starting point to the destination point. Hence, in this part, we consider the different number of joint service requests for each AV in these three cities. Based on the objective function formulated in (18), the optimal value follows the trend as the change of the number of participating AVs. The computational time increases linearly with the number of service requests. Besides, the optimality of the distributed solution is not affected by the number of service requests. This is because increasing service requests do not influence the number of sub-problems created and thus the solution space does not change.

Furthermore, we investigate the change of the average unit cost due to different ratio of logistic and ride-sharing requests in the city of Carolina. Here we set the number of participated AVs to 50, and report the ratio as the number of logistic requests over the number of ride-sharing requests. Here we set the number of ride-sharing requests to one or two. Then, we consider the four different cases with one, two, four, and

TABLE IX
IMPACT OF DIFFERENT RATIO OF SERVICE REQUESTS WITH 50 AVS

Carolina			
Ratio	1	2	4
Average unit cost (US$)	2293.2	2438.8	3094.0
Dodge City			
Ratio	1	2	4
Average unit cost (US$)	5821.2	7392.0	7761.6
Garden City			
Ratio	1	2	4
Average unit cost (US$)	10981.6	12168.8	13723.6

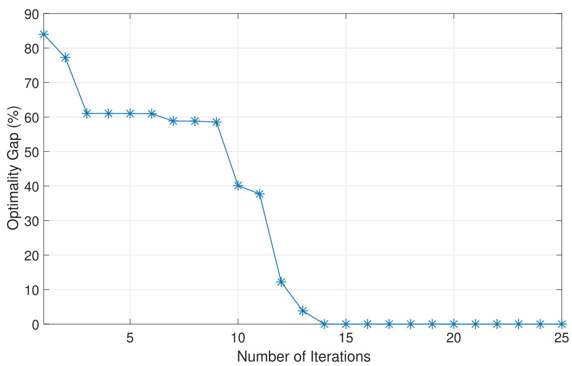

Fig. 4. Convergence of projected gradient decent.

eight logistic requests. The result is presented in Table IX. Apparently, when the number of logistic requests increases, the average unit cost increases, which reflects that the system incurs more operational cost on the provision of the joint service.

F. Convergence of Distributed Solution

It is important to assess the convergence of the devised distributed method, shown in Algorithm 1. To this end, we study the city of Carolina with 300 participating AVs. In addition, we consider the corresponding duality gaps that are computed via projected gradient decent for every iteration. The duality gap is related to the difference of primal and dual objective values.

The result is shown in Fig. 4. One may observe that convergence occurs after approximately 14 iterations. Meanwhile, the duality gap value reaches the tolerance threshold of the stopping criterion in Algorithm 1. This confirms that the devised distributed algorithm is effective in solving the joint problem.

VII. CONCLUSION

In this paper, we proposed a generic AVIS framework for the joint provision of ride-sharing and parcel delivery services. As most AVs are capable of offering effective ride-sharing services, they can simultaneously help supply chain management to further improve the efficiency of ITS with the consideration of city logistics needs. In this paper, we developed a ride-sharing scheme for AVs and designed a parcel delivery strategy such that AV routing constraints were satisfied. The joint optimization of both services was then formulated as a mixed-integer linear programming problem and solved by deriving a distributed method based on Lagrangian dual decomposition. A series of comprehensive simulations demonstrate the effectiveness of the proposed AVIS in three real-world cities, measured in terms of cost and average service time. In addition, the distributed method was shown to successfully reduce the complexity of the problem at hand while generating near-optimal solutions.

In future work, we will investigate how to transform AVIS into a stochastic system to model the uncertainties involved in each service request. We will also explore how to incorporate different types of AVs into AVIS, such as electric public buses and trucks.

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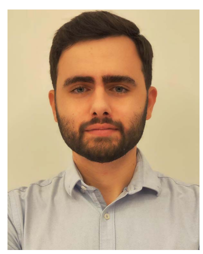

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