Article

Shared Automated Mobility with Demand-Side Cooperation: A Proof-of-Concept Microsimulation Study

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Abstract: Most existing shared automated mobility (SAM) services assume the door-to-door manner, i.e., the pickup and drop-off (PUDO) locations are the places requested by the customers (or demand-side). While some mobility services offer more affordable riding costs in exchange for a little walking effort from customers, their rationales and induced impacts (in terms of mobility and sustainability) from the system perspective are not clear. This study proposes a demand-side cooperative shared automated mobility (DC-SAM) service framework, aiming to fill this knowledge gap and to assess the mobility and sustainability impacts. The optimal ride matching problem is formulated and solved in an online manner through a micro-simulation model, Simulation of Urban Mobility (SUMO). The objective is to maximize the profit (considering both the revenue and cost) of the proposed SAM service, considering the constraints in seat capacities of shared automated vehicles (SAVs) and comfortable walking distance from the perspective of customers. A case study on a portion of a New York City (NYC) network with a pre-defined fleet size demonstrated the efficacy and promise of the proposed system. The results show that the proposed DC-SAM service can not only significantly reduce the SAV's operating costs in terms of vehicle-miles traveled (VMT), vehicle-hours traveled (VHT), and vehicle energy consumption (VEC) by up to 53, 46 and 51%, respectively, but can also considerably improve the customer service by 30 and 56%, with regard to customer waiting time (CWT) and trip detour factor (TDF), compared to a heuristic service model. In addition, the demand-side cooperation strategy can bring about additional system-wide mobility and sustainability benefits in the range of 4–10%.

Keywords: demand-side cooperative shared automated mobility; microscopic traffic simulation; optimal ride matching; environmental sustainability

1. Introduction

Shared and automated mobility has been prevailing and changing the paradigm of next-generation urban transportation systems, leading to disruptive concepts such as Mobility-as-a-Service (MaaS) and transportation network companies (TNCs), such as Uber and Lyft. TNCs have been efficiently identifying the missing links between demands (customers) and supplies (mobility service providers), and bridging them through innovative platforms and smartphone apps to facilitate the completion of mobility needs. In spite of never-ending criticisms to TNCs such as avoiding government regulations and inducing excess traffic demands [1,2], they keep evolving by providing feasible solutions, such as ride-hailing, pooled TNCs, and different tiers of transportation needs [3,4].

Recently, new car-pooling services emerging in major U.S. cities [5] offer the most affordable ride price in exchange for a little walk of customers to/from designated pickup and drop-off (PUDO) locations with respect to their origins and destinations. Such flexibility in PUDO locations can be considered as a demand-side cooperative strategy. It is similar to the travelling salesman problems (TSP) with moving targets, which have been explored

in the field of operation research for years [6,7]. Such flexibility in travel behaviors of customers may impact overall system efficiency and sustainability [8], such as vehicle miles traveled (VMT), emissions, and energy consumption, although the emerging on-demand mobility services rely on many other types of studies, such as studies of existing services, stated preference studies, and policy studies [9]. However, whether the anticipation holds and how much SAM (shared automated mobility) service will be impacted due to the demand-side cooperation is still unknown.

To address all the challenges mentioned above, or in other words to assess the mobility and sustainability impacts of SAM services with demand-side cooperation, this paper proposes a demand-side cooperative (DC) SAM service optimization model and an open-sourced microscopic simulation platform. The DC ride matching is formulated as a capacitated vehicle routing problem with repositioning (CVRPR) and is solved by a commercial solver (Gurobi). Under the operational constraints, such as SAV seat capacities and maximum walking distances, the DC ride matching strategies aims to optimize the overall profit of the proposed SAM service, which considers both maximizing the serving rate (to obtain more revenue) and minimizing the travel distance, travel time, and energy consumption (to reduce the fleet operational cost). The proposed service can potentially benefit the customers and the entire transportation system by reducing the detoured portions and dead-heading time of SAV trips. The proposed DC-SAM is framed in the Simulation of Urban MObility (SUMO), an open-source and multi-modal microscopic traffic simulation tool. It is capable of modeling not only vehicular traffic dynamics in detail but also customer behaviors (including customer–vehicle interactions) via its unique application programming interfaces (APIs), i.e., "TraCI" [10]. This enables the proof-of-concept study of the proposed DC-SAM service in a dynamic environment where the ride matching and repositioning (i.e., re-optimization) are performed continuously as the system evolves (e.g., new on-demand ride requests pop up). In addition, a real-world network of New York City (NYC) is coded and ride demands as well as background traffic are synthesized to evaluate the performance of the proposed DC-SAM service.

Compared to existing studies, the major contributions of this paper involve but are not limited to:

1. Development of a demand-side cooperative (on-demand) shared automated mobility (DC-SAM) service which can further improve system efficiency.
2. Modeling of the proposed system in an open-source and multi-modal microscopic simulation platform in a dynamic environment with more realistic settings, including real-world roadway network, background traffic impacts, SAV dynamics, and customer–SAV interactions. This platform has the potential for extended microscopic traffic modeling and analysis related to MaaS.

The rest of this paper is organized as follows: Section 2 introduces the background information and the relevant literature on SAM modeling and fleet operation. The proposed framework of DC-SAM system and the ride matching algorithm are illustrated in Section 3, followed by a NYC network case study as Section 4. The details of discussion, including comparison study and comprehensive sensitivity analyses are elaborated in Section 5. The last section concludes this paper with further discussion and future work.

2. Background

On-demand shared mobility has been considered as a cost-effective strategy to fulfill transportation demand without compromising traffic congestion, fuel consumption and air quality [11]. In particular, ridesharing refers to the rides in a vehicle among individual travelers (a driver or customer) whose itinerary is in the proximity of both space and time, although the system in which customers may not share the vehicle at the same time can also increase congestion [1,2]. With the emergence of smartphones and the Internet, for-hiring pooled services research and development has focused on online ride-matching programs as well as real-time traveler information delivery. Thanks to both the rapid advances in information and communication technologies and increased concerns for

contemporary transportation issues (e.g., congestion, environment, and parking), more affordable, secure, and accessible Mobility on Demand (MOD) [12], shared ride [13], and pooled TNC services have been provided continuously by transportation network companies (TNCs) via smartphone apps, such as Uber and Lyft [14]. Based on positional elements, Furuhata et al. proposed a systematic classification scheme over the ridesharing patterns and discussed some significant challenges and future directions, mainly from the perspective of matching agencies [15].

Due to the significant progress of autonomous vehicles (AV) in the past decade, the convergence of AV technology and pooled TNC service, i.e., shared automated mobility (SAM) as well as shared automated vehicles (SAVs), has received considerable attention and holds great promise for transforming urban land use as well as alleviating many traffic-related issues in city regions. Some studies started from a limited-scale of SAV deployment or designated transit service scenarios [16,17]. Burns et al. numerically simulated a city-wide SAV fleet operation, where homogeneous trip rates and simplified distance estimation were assumed to reduce computational load [18]. Brownell proposed an autonomous taxi network (ATN) system with a ridesharing option as an alternative transit solution [19]. A simplified agent-based model was proposed by Fagnant and Kockelman to estimate the effectiveness of SAVs by replacing the fleet of private vehicles in Austin, TX area [20]. Later on, they improved their modeling capabilities by introducing the dynamic ridesharing option [21]. Similarly, Zhang et al. developed an agent-based model for SAV operation with the consideration of dynamic ridesharing to explore its impacts on urban parking demand (with the potential to eliminate up to 90% of parking spaces) [22]. Recent studies evaluated the opportunities of the SAM system to serve as the feeder to facilitate public transit operation [23]. When integrating with transportation electrification, the shared autonomous electric mobility (SAEM) system may have profound impacts on both transportation and power grid operations [24–26]. However, almost all the modeling efforts are limited to numerical analysis or agent-based approaches, which cannot represent the traffic dynamics in realistic manner or the delicate interactions between different road users (including both vehicles and customers). Very few studies have implemented the ridesharing models in a microscopic simulation environment. Alam and Habib used VISSIM to simulate the impacts of SAV operation in Halifax, Canada, but a rule-based SAV dispatch algorithm was deployed for simplicity, and the results are far from being optimal at the system level [27].

From a mathematical perspective, the dynamic ridesharing (DRS) problem can be categorized into the well-known vehicle routing problem (VRP), or more specifically dynamic VRP [28–30]. Due to the computational complexity of VRP, a myriad of studies have been focused on developing efficient heuristic approaches to solve DRS problems under different scenarios [31,32]. Furthermore, with the introduction of mobile apps and improved services from TNCs, variants of DRS problems have emerged. Wang considered a DRS problem where drivers or riders may accept or reject the ride-matching assignment provided by the system [33]. Simonetto et al. proposed a computationally efficient dynamic ridesharing algorithm based on a linear assignment problem and federated optimization architecture [34]. In a follow-up study, they examined the impacts of cooperation and competition between ridesharing companies through the Mobility-as-a-Service (MaaS) platform, and showed that the competition could worsen the on-demand mobility service, especially in the presence of customer preferences [35]. To improve system efficiency, Coltin and Veloso proposed a heuristic algorithm to coordinate ridesharing routes and matching, which may smoothly transfer customers between different vehicles [36].

Most of the aforementioned DRS studies, however, assumed door-to-door services. Only a few consider more flexible pickup and drop-off (PUDO) locations, which may potentially provide system-wide benefits for the ridesharing service due to the demand agglomeration effects [37]. Li et al. developed an enhanced ridesharing system where the users may be collectively picked up or dropped off, and the preliminary numerical study showed that the proposed system could improve the overall travel time [38]. Zhao et al.

also relaxed the PUDO location constraints in the ridesharing problem and performed a case study in Matlab [39]. Although the results from these studies were promising, their validation was limited to numerical analyses only without considering the dynamic nature of the system. Therefore, modeling and evaluation of the proposed DRS system in a microscopic traffic simulation environment would be very valuable, which is a focus of our paper.

3. System Framework and Methodology

In transportation research, the performance of emerging mobility technologies and services has been evaluated by transportation demand models and traffic simulation tools. Macroscopic or mesoscopic simulation models, focusing on the network or link level traffic dynamics, may not provide detailed behavior on an individual vehicle or customer basis. Agent-based models such as MATSim are able to describe the activities of every agent in a large scale, but not the delicate interactions between them (vehicles and customers) or the traffic dynamics in a realistic manner. Most of the microscopic simulation tools primarily use an old-fashioned vehicle-based paradigm where customers' behavior in a SAM service cannot be well modeled. Some commercial software, such as PTV VISSIM, has attempted to extend the capability of its products with MaaS features [40]. However, it is very challenging to integrate enough flexibility for demand-side behaviors such as movements of pedestrians or customers [38,39]. To the best of our knowledge, a demand-side cooperative shared automated mobility service has never been modeled and evaluated in a simulation platform with a realistic roadway network and sophisticated operational settings. The proposed demand-side cooperative shared automated mobility (DC-SAM) service includes the framework in microscopic traffic simulation and dynamic ride-matching algorithm.

3.1. System Framework in Simulation

The proposed system, built upon a microscopic simulation architecture of SUMO with background traffic, consists of a group of customers, a fleet of shared automated vehicles (SAVs), and a service coordinator. SUMO has been used for describing emerging on-demand shared mobility in several studies [41,42]. The customer's demand is generated randomly over the simulation network. The request information is sent to the service coordinator, including time stamp, location (with privacy consideration), group size, trip origin (if different from the location upon request), and trip destination. As the core of the DC-SAM system, the service coordinator keeps collecting the riding requests from customers and monitoring the states of SAVs (e.g., location, seat availability) as well as network traffic in real time. Then, it determines the optimal ride-matching for each customer–SAV pair and the alternative pickup and drop-off (PUDO) locations, and communicates all this information with designated customers. Once the customers confirm the matched SAVs and PUDO locations (which may be mandated by customers or suggested by the system and may be different from their trip origins and destinations), the service coordinator will deliver walking guidance related to PUDO locations (if applicable) to customers, and itineraries as well as suggested routes to SAVs. The customers follow the shortest distance (walkable) paths and the travel times of walking are calculated by the lengths of walking paths divided by the constant walking speed (5 kph), which is set in SUMO. To this end, customers will proceed until the completion of their trips, and SAVs will follow the system's suggestion (or commands) to provide service. If any SAV completes its service round without receiving further requests, it can be re-positioned to the suggested location by the service coordinator. The system framework, key components (i.e., customers, SAVs, and service coordinator), and associated flowcharts are illustrated in Figure 1.
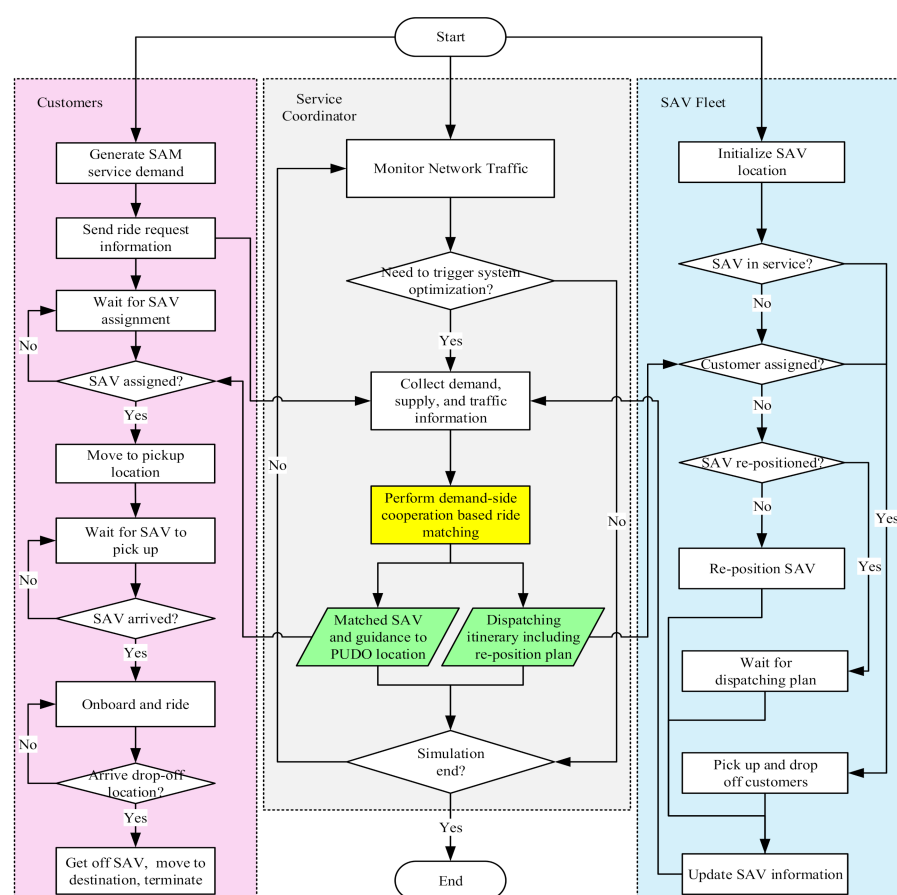
Figure 1. The system framework of demand-side cooperative shared automated mobility (DC-SAM) service.

The proposed DC-SAM service operates in an "online" manner in the microscopic simulation environment. Upon the start of simulation, the service coordinator collects the information from both demand (i.e., customers) and supply (i.e., SAVs) sides. At a certain frequency or within a System Optimization Time Window (e.g., every 120 s), the system performs cooperative (involving multiple customers and multiple SAVs) optimal ride matching, based on up-to-date information on unserved requests and available SAVs. A SAV is available for new customer(s) only if the vehicle has delivered all customers and a new system optimization time window reaches. The procedure continues until all demands are satisfied, or the simulation ends. From the perspective of a customer (demand-side), a random number generator (RNG) is coded to reflect the customer's compliance (cooperation) to accept alternative PUDO locations. For example, if the generated random number is greater than a threshold, the customer will be cooperative and follow the guidance about alternative PUDO locations suggested by the service coordinator. Otherwise, the customer will stick to door-to-door service without demand-side cooperation. In a more sophisticated mode choice model, many factors, such as walking distance penalty, could be considered as one of the future steps in modeling. Once the trip itinerary gets confirmed, the customer will move to the pickup location or stay at the origin to wait for riding on the matched SAV. When the SAV arrives at the drop-off location, the customer will finish the trip instantaneously or walk to his/her own destination. From the perspective of a SAV (supply-side), it follows the ride matching plans and recommended routes as well as re-positioning guidance by the service coordinator, throughout the simulation run to provide the proposed DC-SAM service. Re-positioning of SAV to wait for potential customers is an interesting research topic, and researchers have investigated different strategies and evaluated the energy and mobility impacts [20,43]. For simplicity, the re-positioned locations in this study are chosen based on the information of last round service (e.g., the destinations

of customers). For a more complicated system, these locations may be identified from spatiotemporal predictive analytics of historical SAM service demands [44]. It is also noted that the service fleet is considered "automated" herein because: (1) parameters of SAVs in simulation have been adjusted to model autonomous vehicles (AVs), which are different from background traffic (non-AVs); and (2) all SAVs are assumed to perfectly follow all the guidance provided by the system, including the re-positioning.

3.2. Alternative PUDO Locations

As a critical feature of the proposed DC-SAM service, the alternative PUDO locations of the customer's origin and destination may have multiple candidates depending on the maximum walking distance and surrounding network topology. As shown in Figure 2, a customer *i* is located at the origin and is able to walk from the origin to any place along with all directions on the road network within the maximum walking distance (e.g., 0.5 mile), enclosed by the blue ellipse. Nearby walkable routes are indicated as red solid lines along the blocks. Theoretically, any place on the red lines could be considered as an alternative location for picking up the customer. However, given all the potential travel directions (arrows shown in Figure 2) of a SAV while completing the customer's pickup, only a limited number of key candidate locations within the maximum walking distance need to be considered. The alternative locations for dropping off in the simulation are identified in a similar way. In practice, other factors such as parking restrictions and unsafe streets could be considered for determining alternative PUDO locations. In addition, to facilitate the modeling of cooperation levels by customers (demand-side), origin and destination locations are also included in the candidate PUDO location set.
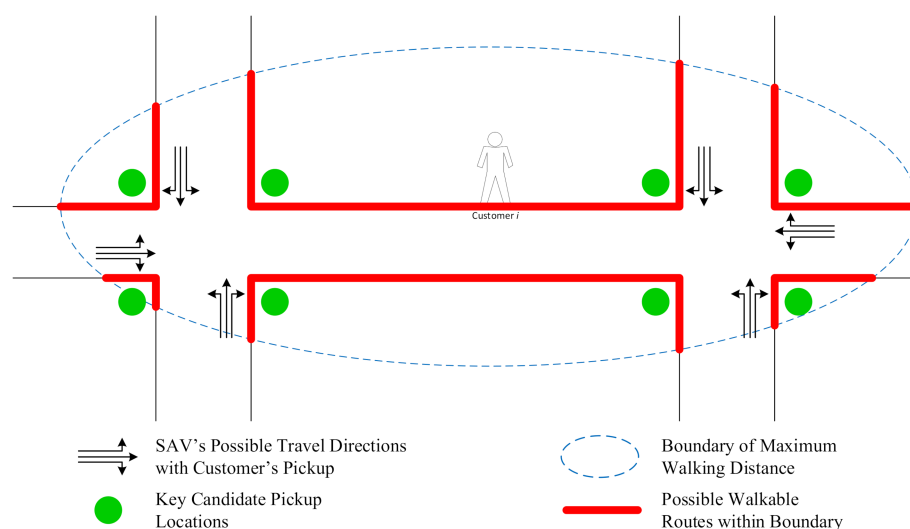
Figure 2. An example illustrating alternative pickup locations.

3.3. Ride Matching

The ride matching procedure generates a dispatching plan for SAVs and determines the PUDO locations for customers, which is a critical component of the proposed system. Optimization models are proposed and implemented in the simulation framework, while a heuristic model of ride matching is also introduced in the following section as the baseline scenario for comparison.

3.3.1. Heuristic Model

This model calculates a ride matching plan according to the spatiotemporal travel information of customers and SAVs in a heuristic manner, which has been used in the early "door-to-door" deployment of SAM services and supply chains [45]. In this model, a spatiotemporal incremental matching algorithm assigns each customer to a SAV and

forms the service sequence. First, the potential customers are sorted by the ride request time ascendingly. The earlier the customer's request time is, the higher the priority is to be served. Then, SAVs are ordered by the route distance to *Customer r* ascendingly. For the nearest SAV *v*, if it is available, *Customer r* will be matched to *SAV v* and both of them are recorded in a customer–SAV mapping dictionary as $M = \{v : [r]\}$. Otherwise, *SAV v* cannot serve *Customer r* and the second nearest available *SAV v'* will be checked until either all potential customers are assigned, or no SAVs are available.

From a SAV viewpoint, it could be assigned with several customers (up to its seat capacity), e.g., $M = \{v : [r_1, r_2, r_3]\}$ for a 3-seat SAV, where the assigned customers are ascendingly ordered by the request time. All customers are delivered in the order of pickup. The algorithm outputs the mapping dictionary *M* for vehicle routing. With that, a First-Come-First-Served (FCFS) logic is applied to determine the PUDO sequence of the SAV. In addition, all customers have to be picked up first and then delivered in the order listed in the customer-SAV dictionary. For instance, for $M = \{v : [r_1, r_2, r_3]\}$, the service sequence of *SAV v* is $p(r_1), p(r_2), p(r_3), d(r_1), d(r_2)$, and $d(r_3)$, where $p(\cdot)$ and $d(\cdot)$ denote the SAV's pickup and drop-off actions, respectively. Based on the sequence, the SAV takes the time-dependent shortest paths (TDSP), which consider the real-time network traffic conditions (e.g., link travel times), to connect PUDO locations.

The main purpose/scope of this heuristic model is to avoid the long customer waiting times for all requests (which is considered as one of the major concerns for pooled TNCs) rather than to maximize the system profit. The heuristic model is severed as a benchmark for comparing with other optimal ride matching models (ODC, Optimization Model with Demand-side Cooperation, and ONDC, Optimization Model without Demand-side Cooperation) proposed in this study. In SUMO, the real-time network traffic condition can be accessed via an application programming interface (API) for shortest path finding. In the real world, such information can be estimated if a large-scale traffic surveillance system is deployed.

3.3.2. Optimization Model with Demand-Side Cooperation (ODC)

The ride matching optimization with demand-side cooperation is modeled as a 0–1 binary integer programming problem with a directed graphic structure shown in Figure 3. In this study, an API is developed in Python for the SUMO simulation to solve this ride matching optimization problem online using the Gurobi Optimizer, which is an efficient solver for integer programming [46]. Before elaborating the model details, parameters and decision variables in the optimization are listed in Table 1. Note that $n_i(j)$ may include $O_{n_i(j)}$ or $D_{n_i(j)}$. Furthermore, D_r^{SAV} is a dummy node for the completeness of the network, i.e., to connect the final drop-off location of last service round with the origin of new service round. Depending on the re-positioning strategy, the cost from $D_{n_i(j)}$ to D_r^{SAV} or from O_r^{SAV} to $O_{n_i(j)}$ may vary.

Table 1. Parameters (PARAM.) and Variable (VAR.) list of ride matching optimization models.

PARAM.	Description
$R_{n_i(j)}$	ride request $R_{n_i(j)} \triangleq \left\{ t_{n_i(j)}, O_{n_i(j)}, D_{n_i(j)}, s_{n(j)} \right\}$
$n_i(j)$	*j*th alternative location of request *i*
$t_{n_i(j)}$	departure time of request *i* at *j*th alternative location
$O_{n_i(j)}$	*j*th alternative pickup location (node) of request *i*
$D_{n_i(j)}$	*j*th alternative drop-off location (node) of request *i*
$s_{n_i(j)}$	size (i.e., the number of customers) of request *i* at *j*th alternative location;
O_r^{SAV}	origin of *r*th SAV

Table 1. *Cont.*

PARAM.	Description
D_r^{SAV}	destination of rth SAV
C_r^{SAV}	capacity of rth SAV
$c_{r,n_i(j),n_k(l)}$	cost (e.g., travel distance) for rth SAV traveling from node $n_i(j)$ to node $n_k(l)$
$p_{r,n_i(j)}$	revenue of jth alternative location of request i served by rth SAV
M	total number of requests
R	total number of SAVs
N_i	total number of alternative locations of request i
Var.	**Description**
$y_{r,n_i(j)}$	binary variable indicates that the rth SAV visits jth alternative location of request i (1-visited; 0-not visited)
$x_{r,n_i(j),\,n_k(l)}$	binary variable indicates that the rth SAV selects a route from node $n_i(j)$ to node $n_k(l)$ (1-selected; 0-not selected)
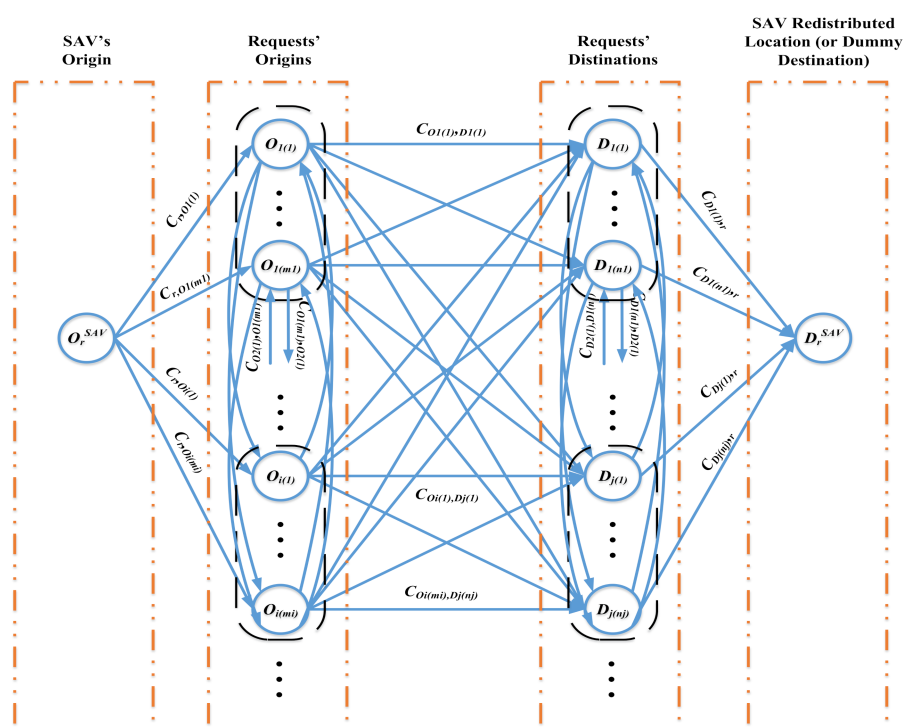
Figure 3. A directed graphical structure of demand-side cooperative dispatching formulation for one SAV.

The objective of the ride matching problem is to maximize the profit of the proposed DC-SAM service, considering both the revenue (positive) and the travel cost (negative) of the SAV fleet. Depending on the SAV availability, each ride request may or may not be served within the instant system optimization time window right after the request generation. For those ride requests that cannot be served instantly, they will be logged in the request list for the ride matching in the future system optimization time window. In the simulation, no waiting time tolerance is set for each request, so all the requests would be served eventually if the simulation time is long enough.

The problem is formulated as follows:

$$
\begin{aligned}
\max \sum_{r=1}^{R} \sum_{i=1}^{M} \quad & \sum_{j=1}^{N_i} p_{r,n_i(j)} \cdot y_{r,n_i(j)} \\
- \Bigg[& \sum_{r=1}^{R} \sum_{i=1}^{M} \sum_{j=1}^{N_i} c_{r,O_r^{SAV},O_{n_i(j)}} \cdot x_{r,O_r^{SAV},O_{n_i(j)}} \\
& + \sum_{r=1}^{R} \sum_{i,k:i\neq k}^{M} \sum_{j=1}^{N_i} \sum_{l=1}^{N_k} c_{r,O_{n_i(j)},O_{n_k(l)}} \cdot x_{r,O_{n_i(j)},O_{n_k(l)}} \\
& + \sum_{r=1}^{R} \sum_{i,k}^{M} \sum_{j=1}^{N_i} \sum_{l=1}^{N_k} c_{r,O_{n_i(j)},D_{n_k(l)}} \cdot x_{r,O_{n_i(j)},D_{n_k(l)}} \\
& + \sum_{r=1}^{R} \sum_{i,k:i\neq k}^{M} \sum_{j=1}^{N_i} \sum_{l=1}^{N_k} c_{r,D_{n_i(j)},D_{n_k(l)}} \cdot x_{r,D_{n_i(j)},D_{n_k(l)}} \\
& + \sum_{r=1}^{R} \sum_{i=1}^{M} \sum_{j=1}^{N_i} c_{r,D_{n_i(j)},D_r^{SAV}} \cdot x_{r,D_{n_i(j)},D_r^{SAV}} \Bigg]
\end{aligned}
\tag{1}
$$

Subject to

$$
\begin{aligned}
\sum_{r=1}^{R} y_{r,O_{n_i(j)}} \leq 1, \ \forall i,\, j \\
\sum_{r=1}^{R} y_{r,D_{n_i(j)}} \leq 1, \ \forall i,\, j
\end{aligned}
\tag{2}
$$

(1)   Each alternative location node, e.g., the *j*th alternative location for the *i*th request, in either Origin (for pickup) set or Destination (for drop-off) set, is visited at most once by whichever SAV.

$$
\sum_{i}^{M} \sum_{j=1}^{N_i} s_{n_i(j)} \cdot y_{r,O_{n_i(j)}} \leq C_r^{SAV}, \ \forall r
\tag{3}
$$

(2)   For the *r*th SAV, the number of pickup nodes visited within the same service round (or system optimization time window) should not exceed its associated capacity, C_r^{SAV}

$$
\sum_{i}^{M} \sum_{j=1}^{N_i} x_{r,O_r^{SAV},O_{n_i(j)}} \leq 1, \ \forall r
\tag{4}
$$

(3)   From its origin, the *r*th SAV will visit at most one pickup location.

$$
\sum_{i:i\neq k}^{M} \sum_{j=1}^{N_i} x_{r,O_{n_i(j)},O_{n_k(l)}} + x_{r,O_r^{SAV},O_{n_k(l)}} = y_{r,O_{n_k(l)}}, \ \forall k,l,r
\tag{5}
$$

(4)   For any SAV, each pickup node has at most one incoming link, which equals to $y_{r,O_{n_k(l)}}$.

$$
\sum_{k:\,k\neq i}^{M} \sum_{l=1}^{N_k} x_{r,O_{n_i(j)},O_{n_k(l)}} + \sum_{k}^{M} \sum_{l=1}^{N_k} x_{r,O_{n_i(j)},D_{n_k(l)}} = y_{r,O_{n_i(j)}}, \ \forall i,j,r
\tag{6}
$$

(5)   For any SAV, each pickup node has at most one outgoing link, which equals to $y_{r,O_{n_i(j)}}$.

$$
\sum_{i,\,k}^{M} \sum_{j=1}^{N_i} \sum_{l=1}^{N_k} x_{r,O_{n_i(j)},D_{n_k(l)}} \leq 1, \ \forall r
\tag{7}
$$

(6)   After the *r*th SAV picks up all the customers in the origin node set, it will go to the destination node set. In other words, at most, one link will be set up between the origin node set and destination node set.

$$
\sum_{i:\,i\neq k}^{M} \sum_{j=1}^{N_i} x_{r,D_{n_i(j)},D_{n_k(l)}} + \sum_{i}^{M} \sum_{j=1}^{N_i} x_{r,O_{n_i(j)},D_{n_k(l)}} = y_{r,D_{n_k(l)}}, \ \forall k,l,r
\tag{8}
$$

(7)   For any SAV, each drop-off node has at most one incoming link, which equals to $y_{r,D_{n_i(j)}}$

$$
\sum_{k:\,k\neq i}^{M} \sum_{l=1}^{N_k} x_{r,D_{n_i(j)},D_{n_k(l)}} + x_{r,D_{n_i(j)},D_r^{SAV}} = y_{r,D_{n_i(j)}}, \ \forall i,j,r
\tag{9}
$$

(8)   For any SAV, each drop-off node has at most one outgoing link, which equals to $y_{r,D_{n_i(j)}}$.

$$
\sum_{j=1}^{N_i} y_{r,O_{n_i(j)}} \leq 1, \ \forall i,r
\tag{10}
$$

(9)   For any SAV and any request, there is at most one alternative pickup location selected.

$$\sum_{j=1}^{N_i} y_{r,D_{n_i(j)}} \leq 1 \; \forall i, r \tag{11}$$

(10) For any SAV and any request, there is at most one alternative drop-off location selected.

3.3.3. Optimization Model without Demand-Side Cooperation (ONDC)

To demonstrate the benefits of demand-side cooperation, a similar ride matching optimization problem to ODC is formulated without considering any alternative PUDO locations besides the origin and destination specified by the customer (i.e., "door-to-door" service). Therefore, all the nodes enclosed by the black dashed line in Figure 3. are collapsed into one node. In other words, the Optimization Model without Demand-side Cooperation (ONDC) can be considered as a special case of ODC where both *j*'s and *l*'s in Equations (1)–(10) are reduced to 1.

3.4. Network Output Metrics

The service performance metrics defined in Table 2 are directly computed from simulation results, such as trace data, vehicle stops, customer loading data, and service operation plans. They may describe the level of service, mobility efficiency of SAV fleet, and customers' cooperation efforts, which encompass vehicle miles traveled (VMT), vehicle hour traveled (VHT), trip detour factor (TDF), customer waiting time (CWT), customer walking time (WKT), and customer walking distance (WKM). It is noted that TDF can be considered as a surrogate metric to evaluate the customer's loss (in terms of travel distance) due to the shift from a dedicated service to a ridesharing service. Besides that, vehicle energy consumption (VEC) indicates the energy and/or fuel consumed by the SAV fleets serving all the shared riders or customers in the system. In this study, the fuel consumption and tailpipe emissions are estimated by SUMO, based on the Handbook Emission Factors for Road Transport (HBEFA) [46] where a typical gasoline-powered light-duty vehicle model is adopted.

Table 2. Key service performance metrics.

Metrics	Unit	Description
VMT	Vehicle-mile	Vehicle miles traveled
VHT	Vehicle-hour	Vehicle time traveled in hour
TDF	-	Trip detour factor: customer's actual trip distance under the pooled TNC service divided by the trip distance with dedicated service (based on the time-dependent shortest path).
CWT	Second	Average customer's waiting time; waiting time for the matched vehicle moving to the pickup location and picking the customer up.
WKT	Second	Customer's time spent on walking to/from alternative PUDO locations with respect to the origin and destination.
WKM	Mile	Customer's walking distance to/from alternative PUDO locations with respect to the origin and destination.
VEC	Liter (gasoline)	Vehicle energy/fuel consumption for serving all customers.

4. Case Study

The proposed demand-side cooperative shared automated mobility service (DC-SAM) simulation was implemented and studied in SUMO with the New York City (NYC) network (see Figure 4). The Open Street Map (OSM) provides the detailed roadway network and

default traffic signal plans in the region, which is imported in the SUMO platform. Shared automated vehicles (SAVs), SAV routes, background traffic, and movements of customers (either waiting or on-board) are illustrated in Figure 4.
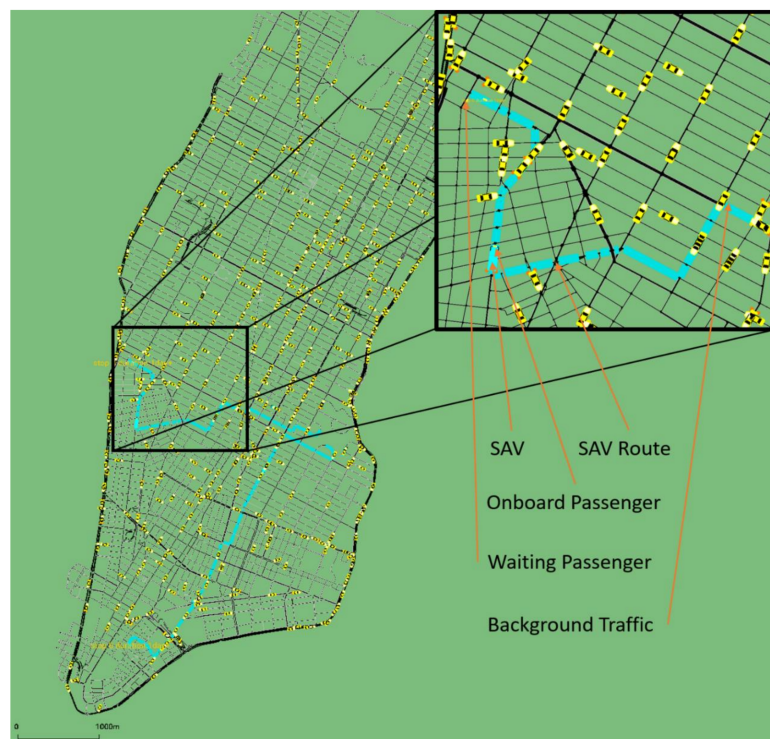
Figure 4. SUMO (Simulation of Urban Mobility) for the New York City network.

The SAM demand was extracted from a New York City Taxi and Uber Trips study [47], which provided a vast amount of individual taxi trips in the city from January 2009 to June 2015. In this paper, a small sample from one taxi company's trip data on 1 June 2015 was selected. The original information of each trip includes pickup and drop-off (PUDO) locations, PUDO times, customer counts, vendor information, and transaction data (i.e., fare). In the simulation, a total of 140 trips were selected as the baseline SAM demand and synthesized according to the PUDO locations (as the surrogates of origins/destinations) and pickup time (as the surrogate of request time).

4.1. Simulation Setup

Four vehicles with three available seats (i.e., the maximum occupancy per vehicle is 3) were set as the SAV fleet to serve the SAM demand over the network. These SAV behaviors were finetuned in the SUMO simulation by adjusting the driver imperfection indicator to be 0 (i.e., perfect driving), and setting the desired time headway to be 1.5 s, which is different from the background traffic of human-driven vehicles (i.e., 2 s). At the beginning of the simulation, these SAVs were assigned to random locations and got ready for the execution of different ride matching models: 1) heuristic matching; 2) optimal matching without demand-side cooperation (ONDC); and 3) optimal matching with demand-side cooperation (ODC). Within every system optimization time window, the service coordinator monitored available SAVs and unserved demands, based on which a designated pickup/drop-off plan was calculated depending on the selected ride matching models. For the optimization models (ODC and ONDC), a high enough revenue (10,000 units, a unit = 1 dollar or mile) was set to incentivize SAVs to serve as many demands as possible. The travel cost from one place to another is proportional to the route distance of the least-duration path, which depends on the time-varying traffic conditions. After ride matching, the designated SAV would move to pick up and drop off customers according to the assigned itinerary. To

guarantee that the demand can be served exhaustedly, a long enough simulation horizon (60,000 steps) was used. In addition, background traffic randomly generated at the rate of one trip per second was introduced into the simulation network uniformly over time. The computing platform to conduct the simulation is set up as follows: CPU—Intel i7 8700; GPU—Nvidia 1660 Ti; OS—Windows 10 version 1909; SUMO 1.2.0; and Gurobi 8.1.1.

It is noted that a small-scale (in terms of optimization problem) test was presented in this paper to prove the concept (i.e., to demonstrate the proposed DC-SAM service). A major concern is the computational efficiency. It is well known that off-the-shelf optimization solvers are not able to address instances with roughly more than 10 vehicles for pooled TNC services with floating targets. In this study, the seat capacity was selected as 3 to be consistent with the setting of a small vehicle. Our trial and error tests showed that four vehicles with capacity of 3 seemed to reach the computational limitation that the Gurobi optimization solver could handle. In addition, the number of alternative PUDO locations would impact the computational time. In this study, each origin or destination of the request in the simulation study has up to 4 alternative locations, including itself. The computational efficiency problem may be solved by more efficient algorithms or more powerful high-performance computing (HPC), which is out of the scope of this paper and will be another important future research direction.

4.2. Determination of System Optimization Time Window

System optimization time window refers to the time interval when all the updated information about riding requests and SAV statuses would be collected for the service coordinator to perform the ride matching. It is considered as one of the most critical parameters that governs the tradeoff between SAM performance and computational efficiency. Sensitivity analyses on this parameter have been conducted to evaluate its impacts. As shown in Table 3, if the time window is short (e.g., 1 s), the service coordinator can respond to the ride request instantly as long as there is any SAV available. This may result in higher overhead in computational time and sub-optimality in terms of system performance because there are less opportunities for SAVs to coordinate with each other for serving the customers. On the other hand, if the time window is too long (e.g., 500 s), many more customers and vehicles will be considered in the optimization which may lead to significant computational burden for the Gurobi Optimizer and unsatisfactory customer experience. In addition, due to the change in traffic dynamics, a longer time window might not guarantee better system performance.

Table 3. Sensitivity analysis results on system optimization time window.

	500 s	300 s	240 s	180 s	120 s	60 s	1 s
VMT (vehicle-mile)	302	309	293	289	**283**	304	293
VHT (vehicle-hour)	31.2	30.1	28.8	28.2	**27.9**	28.1	28.4
TDF	4.5	4.69	4.61	4.55	**4.09**	4.64	4.46
CWT (s)	869	836	806	745	**817**	779	846
WKT (s)	468	479	414	474	**476**	429	513
WKM (mile)	0.48	0.49	0.45	0.49	**0.49**	0.46	0.52
VEC	101.1	96.3	90.0	91.6	**82.2**	103.8	88.7
CPU Time (10^3)	18.3	12.0	11.4	14.1	**9.0**	11.7	12.1

It turns out that for the test scenarios (i.e., 140 SAM trips, 4 SAVs with 3 seats capacity per vehicle, and the given background traffic), the "best" system optimization time window is 120 s in terms of the majority of performance metrics listed in Table 3, such as VMT, VHT, TDF, VEC, and CPU time (in second). For other parameters, e.g., CWT, WKT, and WKM, the values for the 120 s case are comparable to the others. Therefore, in the following simulation studies, the system optimization time window is set as 120 s.

5. Discussion

5.1. Comparison of Different Ride Matching Strategies

The comparative simulation results across all different ride matching strategies, i.e., heuristic, ONDC, and ODC are shown in Table 4. From the SAV (or supply-side) perspective, both optimal strategies (ONDC and ODC) can remarkably reduce VMT, VHT, VEC, and tailpipe emissions in the range of 43.4 to 53.3%, which indicates that the optimization algorithms are much more efficient and sustainable in terms of serving SAM demands with respect to the heuristic strategy. In addition, the proposed ODC strategy can further improve the shared mobility performance compared to the ONDC strategy. For example, the scenario with ODC can reduce VMT and VHT by 4.3 and 4.5%, respectively, compared to the scenario with ONDC. In terms of environmental sustainability, demand-side cooperation can help further drop down the fuel consumption and pollutant emissions in the range of 2.2–5.0%.

Table 4. Simulation results for three strategies.

Strategy	Performance Metrics									
	VMT	VHT	TDF	CWT	VEC (L)	CO_2 (kg)	CO (kg)	HC (g)	NO_x (g)	PM_x (g)
Heuristic	605.4	51.6	9.24	1159	155.3	361.2	9.33	50.4	150.6	7.06
ONDC	295.6	29.2	4.45	786	86.5	201.1	6.00	31.9	85.7	4.14
ODC	283.0	27.9	4.09	817	82.2	191.1	5.87	31.1	81.5	3.96
ONDC vs. Heur.	−51.2%	−43.4%	−51.8%	−32.2%	−44.3%	−44.3%	−35.7%	−36.7%	−43.1%	−41.4%
ODC vs. Heur.	−53.3%	−45.9%	−55.7%	−29.5%	−47.1%	−47.1%	−37.1%	−38.3%	−45.9%	−43.9%
ODC vs. ONDC	−4.3%	−4.5%	−8.1%	3.9%	−5.0%	−5.0%	−2.2%	−2.5%	−4.9%	−4.3%

From the customer (demand-side) perspective, the results show that even without demand-side cooperation, the optimal ride matching algorithm can significantly decrease both TDF (by up to 55.7%) and CWT (by up to 32.2%), compared to the heuristic model. The ODC strategy can further reduce TDF by 8.1% compared to the ONDC strategy. It is hypothesized that the scenario with ODC strategy may further reduce the possibility of SAV route detour due to the demand-side cooperation. The average CWTs for both optimization scenarios are comparable (about 13 min), which are a bit higher than those from TNC waiting time studies due to the sparsity of both demands and supplies in the large urban network in this proof-of-concept study.

5.2. Sensitivity Analysis

5.2.1. SAM Service Demand

To inspect the sensitivity of system performance with respect to SAM service demands, simulation runs with different numbers of requests (where the seat capacity is 3), i.e., 20 trips, 60 trips, and 140 trips (benchmark), were tested and the results are shown in Table 5. It can be observed that the performance metrics fluctuate within an acceptable range, which provides some evidence for the system robustness.

Table 5. Simulation results for ODC (Optimization Model without Demand-side Cooperation) scenarios with different demand levels.

Metrics	20 trips	60 trips	140 trips (Benchmark)
VMT (vehicle-mile)	58.34	133.74	283.0
VHT (vehicle-hour)	8.30	15.25	27.9
TDF	4.53	4.26	4.09
CWT (s)	800	854	817
WKT (s)	480	464	476
WKM (mile)	0.48	0.47	0.49
VEC (L)	27.1	51.1	82.2
CO_2 (kg)	63.0	118.9	191.1
CO (kg)	2.54	4.43	5.87
HC (g)	13.0	22.8	31.1
NO_x (g)	27.4	51.3	81.5
PM_x (g)	1.41	2.59	3.96

As SAM service demand increases, VMT, VHT, and environment-related metrics (such as VEC and tailpipe emissions) increase correspondingly under the same supply capability as expected. For TDF, an apparent decline trend can be seen as the demand level increases. A hypothesis is that higher chances to coordinate the PUDO demands would be anticipated in system optimization with the increase of requests. For other metrics, including CWT, WKT, and WKM, no monotonic patterns (either decrease or increase) are observed, which may be caused by random trip OD locations in such a sparse demand–supply scenario.

5.2.2. Vehicle Capacity

Vehicle capacity is another vital operational parameter that can impact the service performance. The sensitivity analysis may provide some insight for early deployment of the proposed DC-SAM service with suitable vehicle size. Different seat capacities of SAVs (i.e., 1, 2, and 3 seats) were examined and the results are shown in Table 6. Please note that all simulation scenarios here assume 140 trips, 120 s system optimization time window, and 4 SAVs.

Table 6. Simulation results for ODC in different seat capacities.

Metrics.	1 seat	2 seats	3 seats (Benchmark)
VMT (vehicle-mile)	427.5	345.8	283.0
VHT (vehicle-hour)	43.4	33.4	27.9
TDF	2.53	3.49	4.09
CWT (second)	445	627	817
WKT (second)	384	399	476
WKM (mile)	0.43	0.44	0.49
VEC (liter)	122.0	103.2	82.2
CO_2 (kg)	283.7	240.0	191.1
CO (kg)	10.06	7.94	5.87
HC (g)	52.3	41.5	31.1
NO_x (g)	122.3	102.6	81.5
PM_x (g)	6.12	5.05	3.96

According to the simulation results, as the seat capacity grows, most performance measures, such as VMT, VHT, VEC, and pollutant emissions, decrease due to the improvement of supply-side capability and potential system efficiency with optimal ride-matching. Others, e.g., TDF, CWT, WKT, and WKM, increase due to more cooperative efforts being required from the customer side. In particular, for those scenarios with "1 seat", the situation can be considered as the automated "car-sharing" service dedicated to single origin-destination pair. When comparing "1-seat" scenarios with the benchmark pooled TNC services (i.e., "3-seat" scenarios), the experiment results indicate that VMT, VHT,

and environment-related metrics increase by the range of 48.4–71.4%, but those demand-side related metrics (including TDF, CWT, WKT and WKM) get reduced by the range of 12.2–45.5% due to more dedication to the service.

6. Conclusions and Future Work

6.1. Theoretical and Practical Implications

In this study, a demand-side cooperative shared automated mobility (DC-SAM) service framework was developed to allow the customers (i.e., demand-side) to relax their pickup and drop-off (PUDO) locations for improving the overall system efficiency (e.g., reducing the detouring effects of SAVs at the cost of very limited walking loads from customers). The problem was formulated as a binary integer programming and solved by using Gurobi, a commercial optimization solver. The model was implemented in an innovative SUMO-based SAM simulation platform which enables optimal ride matching in an online manner via application programming interfaces (APIs). Results from the preliminary simulation study indicated that the proposed system can significantly reduce the SAV's operating costs in terms of vehicle-miles traveled (VMT), vehicle-hours traveled (VHT), vehicle energy consumption (VEC), and other pollutant emissions, and improve the quality of service by reducing the customer waiting time (CWT) and trip detour factor (TDF), compared to the heuristic algorithm. For example, according to Table 4, VMT, VHT, and VEC can be reduced by 53.3, 45.9 and 47.1%, respectively, and CWT and TDF decrease by 29.5 and 55.7%, respectively, when using the proposed ODC strategy. In addition, the simulation study showed that more benefits can be obtained by enabling the cooperative efforts from customers under the optimal ride matching strategies with demand-side cooperation. The range of mobility and environmental benefits may vary from 2.2 to 8.1%, depending on the specific metrics. Based on the unique microscopic traffic simulation platform built in this study, we extensively evaluated the proposed system under a variety of settings, such as the number of service requests and SAV's maximum occupancy. It should be noted that the developed microscopic platform can lay a good foundation for further pursing research related to multi-modal operation (e.g., curbside management) and applications of emerging transportation technologies (e.g., connected and automated vehicles).

6.2. Limitations and Future Work

There are several limitations about the current work which will serve as our future research directions to improve this work.

- The simulation scenario and mode choice model are simplified. As one of the future steps, the optimization algorithm and simulation platform will be extended to handle more complex and realistic scenarios, such as cancellations of request, considering customers' patience and preferences for waiting or walking in the mode choice model.
- Another limitation is the computational efficiency. Due to the nature of the problem (i.e., NP-hard), applying a commercial optimization solver (Gurobi in this study) may not be efficient enough for large-scale studies. Developing a meta-heuristic algorithm (balancing between optimality and computational efficiency) to solve the large-scale ride matching problem considering demand-side cooperation should be a key direction of future research.
- Other emerging and shared modes can be integrated into the current framework, such as fixed-route ridesharing services or micro-mobility services (e.g., e-scooters, mopeds). The proposed simulation platform is flexible enough to accommodate all these modes.
- Integration of zero-emissions vehicle operation, such as the combination of shared autonomous electric vehicles with the management of charging facilities, will be another interesting and important topic for further investigation, as transportation electrification is considered as one of the major global trends in the not-too-distant future.

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