# Assessing the operational performance of ridesharing-enabled shared autonomous vehicles fleets

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## Short summary

Shared autonomous vehicles (SAVs) are quickly spreading in major cities and may become a preferred mobility solution in the near future. Dynamic ridesharing (DRS) is envisioned to enhance the performance of SAV systems by increasing vehicle occupancy and lowering empty vehicle kilometres travelled (VKT). Nonetheless, existing literature assesses the impact of DRS-SAV utilising unrealistic traffic models or heuristic matching and pricing methods. To address this gap, this paper presents a simulation-based service design assessment framework to test real-time SAV operation strategies. Travellers' mode choices are explicitly modelled, and advanced DRS operation strategies, involving optimal matching and pricing, are tested in a mixed-traffic urban network. The results indicate that advanced DRS methods and accounting for travellers' mode choices greatly increase the number of served travellers with even smaller VKT, while incurring only a slight increase in waiting and travel time. If properly managed, DRS can significantly reduce the congestion caused by private trips and empty VKT.
**Keywords**: dynamic ridesharing, optimal matching, shared autonomous vehicles, traffic congestion.

## 1 Introduction

It is a prevailing phenomenon nowadays to hail a car via smartphone in many major cities. Transportation network companies, such as Uber, Lyft, and Didi, are operating such services to reshape urban passenger transportation. Furthermore, dynamic ridesharing (DRS) allows passengers to share their trips with other travellers to reduce trip costs. The combined convenience and cost-effectiveness of on-demand services including ride-hailing and DRS are expected to attract travellers. Nonetheless, the operational challenges posed by DRS hinder its widespread adoption (Furuhata et al., 2013).

Shared autonomous vehicles (SAVs) act as enablers of more efficient service operations and network efficiency in the context of existing ridesharing norms. Transportation network companies can employ SAVs to lower operational costs and increase profits, whereas, compared to human drivers, (S)AVs can accurately perform complicated operational tasks, such as routing and rebalancing (Nahmias-Biran et al., 2019). Furthermore, the efficient utilization of DRS by SAVs has great potential to reduce vehicle kilometres travelled (VKT), thereby counteracting possible detours (Fagnant & Kockelman, 2018). Besides, SAVs are envisioned to benefit travellers (Loeb & Kockelman, 2019), as well as the transportation systems and the environment (Gurumurthy et al., 2019) by reducing the negative externalities of owning and driving a personal car.

Nonetheless, most studies about SAVs and DRS either emphasize fleet operation or traffic simulation. Most operation-focused studies design novel matching (Alonso-Mora et al., 2017; Hyland & Mahmassani, 2018) and pricing (Zhou et al., 2023) strategies, which are then tested in simulation environments considering simplistic traffic conditions, such as static or historical travel time. On the other hand, large-scale simulation-based studies (Gurumurthy et al., 2019; Räth et al., 2023) commonly employ rule-based operation methods to evaluate the impact of SAVs on traffic. However, such methods may underestimate the efficacy of DRS and yield pessimistic results. At the early stage of SAV introduction, both human-driven vehicles and AVs are expected to coexist

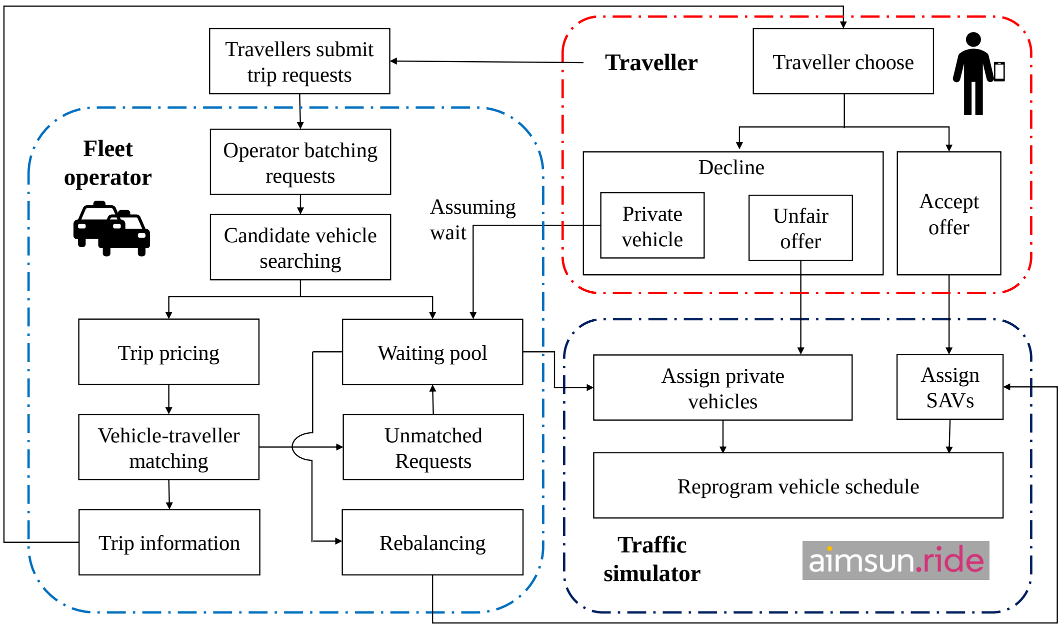



Figure 1: Agent-based DRS-SAV system simulation framework

in the network, which complicates the traffic simulation. Given that this transition period is expected to last for a relatively long duration (Ghiasi et al., 2017), yet little is known about it, it is meaningful to bridge the existing gap by simulating the operation of SAVs in mixed traffic. To capture the details of SAV operations and their interaction with surrounding traffic, a meso- or microscopic traffic simulator is necessary to track vehicle movements. In short, a comprehensive analysis encompassing traffic congestion, user acceptance, and fleet service efficiency in the context of SAV-enabled ridesharing remains unknown. In this study, we attempt to address these research gaps by leveraging advanced assignment and pricing methods, simulating the real-time operation of an SAV fleet in mixed traffic, and considering the travellers' mode choice.
The remainder of the paper is structured as follows: Section 2 describes the simulation framework, elaborating on each of its components; in Section 3, traffic simulation experiments are conducted to evaluate different operation strategies; Section 4 offers an explicit analysis and discussion of the obtained results; finally, Section 5 concludes the paper and suggests avenues for future research.

## 2 Methodology

### *Simulation framework*

As depicted in Fig. 1, the travellers submit their requests online. Next, the fleet operator batches the received requests within a fixed time interval and searches candidate vehicles for each request based on the pickup time. Then the operator calculates the trip fare according to the vehicle schedule associated with each potential vehicle-traveller pair. Note that the route insertion method is adopted to update vehicle schedules in DRS. Once the vehicle schedule and trip fare are determined, the operator proceeds to finalise the vehicle-traveller matching and delivers the trip information to the traveller.
Upon receiving the offer, the traveller, based on the presented price and travel time, can either accept or decline the ride. We assume an unfair pricing plan would lead the traveller to leave the system and use a PV instead. In this context, the unfair price refers to the ridesharing price that disregards the traveller's detour and shared distance. We refer readers to Zhou et al. (2023) for an in-depth explanation of the fairness-aware pricing method. On the other hand, we assume travellers who choose PV over SAV do not leave the system directly. Instead, these requests remain in the waiting pool, considering the possibility of re-assignment. Moreover, due to supply-demand imbalances, idle vehicles may remain in a low-demand region and are unable to serve future requests. To address this, we implement the rebalancing algorithm from Alonso-Mora et al. (2017) to assign idle SAVs to unmatched travellers. Lastly, if the waiting time exceeds the traveller's threshold, a private AV is programmed to fulfil the request.

***Traveller***

Travellers submit their requests, providing travel origin and destination, maximum waiting time and acceptable detour time. For each traveller $r \in R$, the maximum waiting time is $\Omega_r$. Besides, the traveller arrival deadline $\Delta_r$ is defined as an upper bound of arrival time. We employ a discrete choice model (Ben-Akiva & Lerman, 1985) to predict the traveller's mode choice decision. Similar to Zhou et al. (2023), we utilise the following formulations to calculate the utility of different travel modes:

$$f_{\mathrm{PV}} = f^0_{\mathrm{PV}} + f^v_{\mathrm{PV}} \cdot d_{\mathrm{PV}} \tag{1}$$

$$u_{\mathrm{PV}} = \beta_{\mathrm{PV}} + \beta_t \cdot t_{\mathrm{PV}} + \beta_f \cdot f_{\mathrm{PV}} \tag{2}$$

$$u_{\mathrm{SAV}} = \beta_{\mathrm{SAV}} + \beta_t \cdot t_{\mathrm{SAV}} + \beta_f \cdot f_{\mathrm{SAV}} \tag{3}$$

where $f^0_{\mathrm{PV}}$ and $f^v_{\mathrm{PV}}$ are fixed cost per trip and variable costs per kilometre; $f^0_{\mathrm{PV}}$ represents the depreciation fare per trip, while $f^v_{\mathrm{PV}}$ indicates the fuel consumption expense. Besides, $d_{\mathrm{PV}}$ is the private trip distance and $f_{\mathrm{PV}}$ amounts to the private trip cost. $\beta_{\mathrm{PV}}$ and $\beta_{\mathrm{SAV}}$ are model-specific constants to reflect the inherent trip qualities of private vehicles and SAV, respectively; $\beta_t$ and $\beta_f$ represent the marginal disutility of travel time and trip fare; $t_{\mathrm{PV}}$, $t_{\mathrm{SAV}}$, and $f_{\mathrm{SAV}}$ are travel time and trip fare for private and SAV trip respectively. Travellers either accept the SAV offer or decline it based on the trip utility.

***SAVs fleet operator***

## Candidate vehicle-traveller match searching and pricing

The set of SAVs is denoted by $V$ and indexed by $i$ while the set of batched travellers is denoted by $R$ and indexed by $j$. Following Simonetto et al. (2019), we enforce a one-to-one vehicle-traveller match in the current batch. Although assigning one vehicle to multiple travellers is restricted within a single batch, ridesharing is achieved via cross-batch trip combination. This approach ensures that the formulated problem can be solved efficiently and is scalable to accommodate large-scale demand. For each traveller $r_j$, a set $M_j \subset V$ candidate vehicles from $V$ are identified and filtered by the pickup time. Furthermore, we insert the new traveller $r_j$'s origin $O_{r_j}$ and destination $D_{r_j}$ into the candidate vehicle's schedule $S = \{O_{r_1}, ..., O_{r_j}, ..., D_{r_1}, ...D_{r_j}\}$. The optimal route insertion for each vehicle is the one with the minimum travel time.
For solo trips, we adopt the conventional taxi fare structure to calculate the fare $f^{\mathrm{solo}}_r$:

$$f^{\mathrm{solo}}_r = f_0 + f_t t_r + f_d d_r, \tag{4}$$

where $f_0$, $f_t$, and $f_d$ denote base, time, and distance fare rates, respectively, while $t_r$ and $d_r$ are the solo trip time and distance, respectively.
For a ridesharing trip, the trip fare $f^{\mathrm{share}}_r$ is calculated via:

$$f^{\mathrm{share}}_r = \Phi_r \cdot \hat{f}_r, \tag{5}$$

where $\hat{f}_r$ denotes the previous price before route insertion. Additionally, $\hat{f}_r = f^{\mathrm{solo}}_r$ for the new request $r$. The multiplicative discount function $\Phi(\cdot)$ accounts for the traveller's detour rate, the number of co-riders and shared trip distance. Readers are referred to Zhou et al. (2023) for a detailed explanation. Note that the trip fares for those assigned in the earlier stages are changed if the trip is shared with the new traveller. We assume the travellers would automatically accept the updated price only if it is lower than the original price.

## Vehicle-traveller matching

Given the potential vehicle-traveller pairs, the operator determines the optimal assignment, deciding which vehicle should serve which traveller's request. In this paper, we compare two matching strategies: greedy matching and optimisation-based matching. Greedy matching pairs a traveller with a candidate vehicle based on minimum travel time. Once a vehicle is selected, it is removed from the available vehicle set to ensure a one-to-one match. On the other hand, an integer linear optimisation model is modified based on Zhou et al. (2023) to determine the optimal vehicle-traveller matching.

We first define the ridesharing profit $\pi_{S,v}$ for vehicle $v$ as the marginal profit incurred each time a new traveller enters, which is calculated via

$$\pi_{S,v} = (\sum_{r \in S} f_r^{\text{new}} - C_{S,v}^{\text{new}}) - (\sum_{r \in \hat{S}} \hat{f}_r - C_{\hat{S},v}), \tag{6}$$

where $S$ denotes the set including all assigned travellers except those who have reached their destination, $\hat{S}$ represents the same set before the current traveller joins, $C_{\hat{S},v}$ and $C_{S,v}^{new}$ indicate the total trip cost for serving $\hat{S}$ and $S$, respectively.

$$\max_x \sum_r \sum_{v \in V_r} \pi_{S,v} x_{r,v} - \gamma(|R| - \sum_r \sum_{v \in V_p} x_{r,v}) \tag{7}$$

subject to

$$\sum_v x_{r,v} \leq 1, \quad \forall r \in R \tag{8}$$

$$\sum_r x_{r,v} \leq 1, \quad \forall v \in V_r \tag{9}$$

$$x_{r,v} \in \{0, 1\}, \tag{10}$$

where $V_r$ represents the candidate vehicle set for traveller $r$; $x_{r,v}$ is a binary variable that equals 1 if vehicle $v$ is assigned to serve traveller $r$ and 0 otherwise; the parameter $\gamma$ is a unit penalty cost for each unserved traveller; and $|R|$ denotes the number of travellers that wait to be served. Therefore, the multiobjective function (7) jointly maximises the profit and accounts for a penalty function for unserved travellers, while the constraints guarantee a one-to-one match. By relaxing binary variables $x_{r,v}$ to continuous, the above optimisation problem can be solved efficiently with state-of-the-art solvers.

***Traffic simulator***

Aimsun Ride is a simulation platform for planning towards new and primarily demand-responsive mobility in urban environments. It is an agent-based demand-supply interaction framework for multimodal and multi-operator fleet-based service systems, coupled with the Aimsun Next's multi-class mesoscopic traffic simulator (Aimsun, 2023. [Online]). It should be noted that an operator in this context refers to a service provider or fleet manager. In terms of the traffic model, the well-known car-following model based on the Gipps model (Gipps, 1981, 1986) is implemented in Aimsun Next's mesoscopic simulator.

## 3 Case study

***Simulation setup***

The SAV fleet movement is simulated in Aimsun Next (Casas et al., 2010), where it interacts with other human-driven vehicles. To achieve this, a dynamic traffic assignment model (DTA) has been built and calibrated for the city of Tallinn. The calibration has been carried out for the morning peak hours (07:00-10:00) against detector measurements (Agriesti et al., 2023).
The network itself covers an area of $\sim 240\ km^2$, includes $\sim$ 33000 sections and $\sim$ 15600 nodes. The number of centroids is 610. At the beginning of the simulation, 3050 four-seat SAVs are evenly distributed across the network, with five vehicles at each centroid. We simulate a two-hour morning peak. In total, 34750 requests need to be served. Unserved requests due to exceeding the maximum waiting time or unfair pricing are assumed to use private cars instead. Note that the original travel data lack parameters, such as maximum waiting time and latest arrival time, we synthesise these data based on Zhou et al. (2023) and Jiao & Ramezani (2022), as shown in Table 1. The utility parameters in Equation 1, 2 and 3 are set as $f_{pv}^0 = 6$ €, $f_{pv}^v = 0.9$ km/€, $\beta_{pv} = \beta_{SAV} = 0$, $\beta_t = 0.48$ and $\beta_f = 3.2$, modified based on Gurumurthy et al. (2019); Jiao & Ramezani (2022). In Equation 5, we have $f_0 = 2.5$ €, $f_t = 0.2$ €/min ,$f_d = 0.6$ €/km (Amigo Taxi Design, 2023). Finally, we set $\gamma = 2$ €/pax and discount parameter to 0.2 (Zhou et al., 2023).

Table 1: Traveller parameters setting

| Parameter | Unit | Mean | stdev | Lower bound | Upper bound |
|---|---|---|---|---|---|
| Maximum Waiting time | [min] | 7 | 2 | 5 | 15 |
| Acceptable detour time | [min] | 10 | 2 | 0 | 20 |

Table 2: Scenarios of different strategies

| Strategy | Ridesharing | Assignment | Pricing |
|---|---|---|---|
| S1 (Baseline) | No | Nearest | Taxi |
| S2 | Yes | Minimise travel time | mt-share |
| S3 | Yes | Minimise travel time | Fairness-aware |
| S4 | Yes | Optimisation-based | mt-share |
| S5 | Yes | Optimisation-based | Fairness-aware |

***SAV fleet operation strategies for comparison***

To evaluate how fairness-aware price-based optimization affects the performance of DRS services and its influence on congestion, we designed five scenarios. Table 2 shows the different components of each scenario, as follows:
S1 serves as the baseline scenario without ridesharing, where the nearest idle vehicle is assigned to serve each request, and the trip price is calculated via Eq. (5), representing a conventional taxi fare. S2 enhances S1 by allowing ridesharing, while the vehicle-traveller pairs are formed using a simple heuristic method, consisting of assigning the vehicle that results in the minimum total travel time after inserting the new traveller's origin and destination. Besides, the mt-share method is a common pricing method for dynamic ridesharing. Note that the original mt-Share method (Liu et al., 2021) involves a complete framework for dynamic ridesharing, from candidate vehicle searching to probabilistic routing, whereas, in this paper, the proposed pricing method is utilized only to fairly split the ridesharing benefit between co-riders. A detailed algorithm for computing the ridesharing price using the mt-share method can be found in the appendix of Zhou et al. (2023). S3 differs from S2 in terms of the pricing method, where the former employs a fairness-aware pricing method, proposed by Zhou et al. (2023). Furthermore, S4 is designed to improve operation efficiency by incorporating the profit-oriented optimisation model (7)-(10). Finally, S5 combines the optimisation assignment used in S4 with the fairness pricing employed in S3. As all scenarios include a rebalancing module to increase the number of served travellers, it is not displayed in the table.

## 4 Results and discussion

***Fleet performance***

Each scenario introduced in Section 3 is then applied to the network described in Section 3. No other feature of the model is changed, as the initial SAV demand and the background one are employed to initialise each scenario. Table 3 reports the main indicator concerning the performance of the 3050 SAVs across the network and the served requests.
Scenario 5 is the one performing the best on empty VKT (vehicle kilometre travelled), average occupancy and the ratio of VKT and served requests. This suggests that the proposed fairness-aware price-based optimization outperforms all the other combinations. The improvement is not negligible either, as the difference between S5 and the second-best in average occupancy is equal to 0.42, which in turn reduces the empty kilometres travelled to pick up a request. The fewer empty kilometres travelled, the greater the benefits on traffic efficiency (less congestion) and pollution reduction. S4 boasts the second-best performance by the same indicators, suggesting that the optimisation algorithm may play a bigger part in the improvements in S5. It does so by almost halving the kilometres needed for repositioning, which means that the vehicles are able to better spread across the network as they serve the arising requests. This is notable, as the fleet has no

Table 3: Fleet performance - (TTO) meaning travelling to the request and (Reb) meaning rebalancing

| Strategy | Served requests | Total SAV VKT [km] | VKT/served | Empty VKT [km] | | Average occupancy |
|---|---|---|---|---|---|---|
| | | | | TTO | Reb | |
| S1 (Baseline) | 15274 | 239122 | 15.81 | 71994 | 8144 | 1 |
| S2 | 13753 | 228268 | 16.73 | 56716 | 12203 | 1.26 |
| S3 | 15325 | 201513 | 13.72 | 55770 | 12394 | 1.38 |
| S4 | 18041 | 214430 | 12.18 | 60707 | 6582 | 1.49 |
| S5 | 22789 | 206077 | 9.26 | 39494 | 6874 | 1.91 |

Table 4: Service performance

| Strategy | Waiting time [min] | | | In vehicle time [min] | | |
|---|---|---|---|---|---|---|
| | Mean | Median | stdev | Mean | Median | stdev |
| S1 (Baseline) | 6.07 | 4.69 | 6.42 | 16.53 | 12.5 | 13.99 |
| S2 | 6.0 | 3.94 | 7.66 | 22.96 | 18.33 | 17.49 |
| S3 | 5.24 | 3.70 | 6.48 | 23.11 | 17.67 | 18.97 |
| S4 | 7.67 | 5.94 | 6.75 | 22.65 | 17.83 | 17.79 |
| S5 | 6.20 | 4.72 | 6.55 | 24.09 | 20.17 | 18.0 |

prior knowledge of the spatial distribution of the requests. Nevertheless, also the fairness pricing alone in S3 results in a lower (VKT/served request) than in S2. This demonstrates that fair pricing encourages travellers to use ridesharing services. Consequently, 11.4% more travellers are served with 11.7% less VKT.

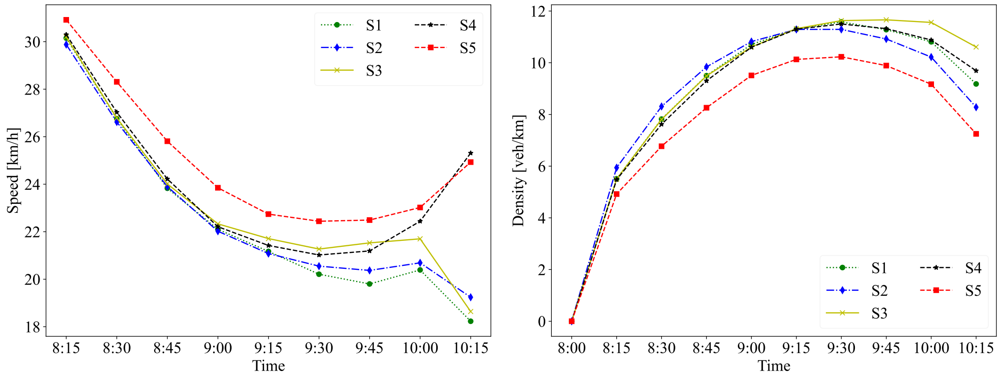
***Service performance***

Table 4 instead reports indicators for the SAV service, representing how effectively the SAV fleet performs while guided by the different algorithms. Indeed, the performance impacts which trips are chosen by the user to be actually served through a shared SAV (as the alternative of employing the private vehicle is always available and becomes more attractive as the travel and waiting time increase for SAV - Section 2). Differently from the initial choice in SimMobility, this choice happens during the traffic assignment and will impact the availability of the SAV vehicles in the following time steps. From Table 3, we observe that the number of travellers served by ridesharing increases from S1 to S5. As a result, all the statistics related to travellers' in-vehicle time increase accordingly with the increase of served requests. Additionally, S4, where the assignment of vehicles to requests follows the optimization algorithm but the pricing is not fairly shared across the ridesharing users, exhibits the longest waiting time. This can be explained by the fact that the mt-share pricing method fails to generate proper ridesharing prices. Due to unfair pricing, travellers leave the system and opt for PVs instead. Consequently, S4 has fewer served travellers. On the other hand, the mt-share pricing method might provide fewer ridesharing benefits, making it less attractive to travellers. Those who choose PVs based on their utility might remain in the waiting pool until the next round of optimisation. Consequently, S4 results in the longest waiting time.

***Network congestion***

Fig. 2 reports how the average vehicle speed and density across the network progresses through the simulated time. The average speed is calculated for all moving vehicles at different time epochs, while the average density is calculated for each link and represents how much the link is loaded per kilometre.

As shown in Fig. 2 (a), the average speed in scenario 5 outperforms that of all other scenarios. This indicates that efficient DRS operation strategies can greatly improve the traffic situation. On the other hand, the average road density is illustrated in Fig. 2 (b). Before 9:15, Scenario 2 has the highest density due to unfair pricing, which incurs more private cars. However, as ridesharing trips gradually finish after 9:15, the density of Scenario 2 decreases rapidly. Surprisingly, scenario




(a) Average speed

(b) Average density

Figure 2: Progression of the average speed and density through the simulation

3 surpasses the other scenarios in density after 9:15. This can be partly attributed to ridesharing trips requiring longer travel times, leading to more vehicles circulating in the latter half of the simulation. However, Scenario 5 consistently maintains lower density throughout the simulation, highlighting the significant reduction in traffic congestion achieved through efficient DRS operation. The higher density in Scenarios 3 and 4 reveals that inappropriate DRS strategies might exacerbate traffic conditions.

## 5 Conclusion

The potential benefits of DRS have been investigated and reported by extensive studies. However, the methodologies in the existing literature either lack a realistic traffic simulator or lack advanced operation strategies. This study aims to address this gap by proposing a real-time DRS framework that integrates an advanced simulator with optimisation-based operation strategies. The simulation results reveal that advanced operation strategies are critical for successful DRS implementation. Intuitive rule-based methods are unable to exploit the potential of DRS and thus limit the utilisation of DRS. Compared to heuristic methods (S2), the optimisation-based matching (S4) can serve 31.2% more travellers with 6.1% less VKT and 1.67 minutes longer waiting time on average. Furthermore, accounting for travellers' mode choices and pricing fairness enhance the system's performance. Comparing S4 with S5, 26.3% more travellers are served with 3.9% less VKT and 1.4 minutes less waiting time. On the other hand, S5 has been proven to significantly reduce vehicle density and thus lead to higher travel speeds and less congestion. Note that all these findings are derived from simulations conducted with a realistic travel time and traffic flow model, enhancing the reliability of the results.

This study provides a benchmark for future DRS-optimisation-related research. The innovative DRS method can be tested via the proposed optimisation-enhanced simulation framework. For instance, the demand-aware routing and rebalancing methods are expected to further improve the DRS efficiency. Besides, another direction is to exploit the future demand information, obtained from historical data or advanced demand-prediction methods, to guide vehicle matching, pricing and rebalancing. Lastly, given the Aimsun Ride allows for multiple operators, it would be interesting to investigate the competition and cooperation strategies between similar service providers.

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