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Autonomous taxi fleet relocation: an agent-based analysis of operational trade-offs

Senlei Wang[a,b,1,*], Gonçalo Homem de Almeida Correia[c], Hai Xiang Lin[a,d]

[a] Delft Institute of Applied Mathematics, Delft University of Technology, Mekelweg 4, 2628 CD Delft, Netherlands (the)
[b] Department of Civil, Environmental and Geomatics Engineering, University College London, Gower Street, London WC1E 6BT, United Kingdom
[c] Department of Transport and Planning, Delft University of Technology, Stevinweg 1, 2628 CN Delft, Netherlands (the)
[d] Institute of Environmental Sciences, Leiden University, Einsteinweg 2, 2333 CC Leiden, Netherlands (the)

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ABSTRACT

Autonomous taxis (AT), which integrate automated vehicles with on-demand services to provide direct door-to-door transport, are transforming urban mobility systems by lowering operating costs and enabling more controlled fleet management. AT services can efficiently match passengers and increase system throughput (e.g., number of served trips). However, AT operations, including passenger matching and proactive relocation, introduce operational uncertainties that could increase costs and travel times due to additional empty vehicle kilometres travelled. We develop an agent-based model to represent vehicle relocations alongside passenger matching and routing for urban AT services and to investigate the AT relocation trade-off between operating costs and operational performance (e.g., wait times, vehicle utilisation). The model is applied to a case study of The Hague, The Netherlands, using detailed road network data and time-dependent origin–destination flows derived from private car trips. Simulation results show that increasing the AT fleet sizes of a company affects service quality of competing operators, resulting in longer average waiting times and up to four additional minutes of travel times due to added traffic. Moreover, relocation generates empty travel, but it occurs during less congested hours, thereby avoiding adding vehicles to road traffic in peak periods. Overall, AT relocation could improve service levels and transport more passengers due to increased availability. An operator using relocation reduces waiting times by about 11% compared to competitors that do not relocate. Profits can also rise by nearly 16% (more than 2,000 euros during morning hours) because more trips are served while the operating costs remain comparatively low.

1. Introduction

The rapid rollout of automated vehicles (AV) equipped with high-level driving automation features (AV level 4 or Level 5) is fundamentally transforming urban mobility. The question is no longer whether AVs should or should not be implemented, but how to operate and organise the transport services they provide in cities (Hancock et al., 2019; Wang et al., 2019). Autonomous taxi (AT) services, which combine AVs with on-demand services, have the potential to provide direct door-to-door transport and enhance city-wide accessibility (Divasson-J. et al., 2025; Manders et al., 2020).

Recent studies focus on the design and modelling of AT operations to assess their energy and mobility impacts (Lau and Susilawati, 2021; Shaheen and Bouzaghrane, 2019; Whitmore et al., 2022). By eliminating paid drivers, AT fleets have the potential to reduce operating costs while leveraging optimised matching and routing to serve passengers more efficiently (Bauer et al., 2018; Liang et al., 2020). At the same time, AT services could introduce new operational uncertainties and external costs; for example, empty AT travel increases vehicle kilometres travelled (VKT), congestion and pollution. The use of automated driving functions presents opportunities to develop intelligent algorithms for efficient passenger matching, routing, and relocation operations (or rebalancing operations) to deliver high-quality services and reduce external costs related to congestion and pollution (Hörl et al., 2019;

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[*] Corresponding author at: Delft Institute of Applied Mathematics, Delft University of Technology, Mekelweg 4, 2628 CD Delft, the Netherlands.
E-mail addresses: senleiwang@gmail.com (S. Wang), G.Correia@tudelft.nl (G.H.A. Correia), H.X.Lin@tudelft.nl (H.X. Lin).

[1] The work was completed at Delft University of Technology and further improved at University College London. The corresponding author is currently employed as a Research and Development Engineer at the National Manufacturing Institute Scotland (NMIS).

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Zhang and Nie, 2018; Zhang and Pavone, 2016).

A central challenge in shared-use AT systems is the spatiotemporal imbalance between vehicle supply (i.e., the distribution of available vehicles) and service demand (i.e., where and when AT service is requested) (Dandl et al., 2019; Illgen and Höck, 2019). Such an imbalance leads to several negative consequences, including reduced service levels, fewer users served or lower profits. Vehicle relocation, in which empty vehicles move to areas with anticipated demand, can help address the imbalance. However, there are trade-offs between the operational cost and operational performance in terms of the service provided to users and vehicle utilisation.

In urban contexts, AT relocation could bring benefits. AT can perform relocation operations more efficiently and at lower costs while improving service quality (e.g., by reducing waiting times). This can be achieved through jointly optimised decisions (e.g., passenger matching, routing) with fully controlled functions (Hyland and Mahmassani, 2020; Alonso-Mora et al., 2017; Hyland and Mahmassani, 2018). AT relocation costs could be lower, mainly by eliminating the need for paid drivers and redistributing capital costs among service users (Loeb and Kockelman, 2019; METZ, 2019). Nevertheless, relocating vehicles could increase empty VKT, leading to higher operating costs and potentially contributing to traffic congestion (Rossi et al., 2018).

Therefore, relocation introduces uncertainties into both the AT fleet operating costs and operational performance. There are trade-offs associated with AT relocation: repositioning idle ATs typically increases VKT and hence operating costs, but it shortens passenger waiting times and transports more passengers. Furthermore, the trade-off becomes more complicated as cities consider different fleet sizes for AT deployment. For instance, a larger fleet can lead to increased fleet operational costs due to under-utilisation and capital costs, but may improve services (e.g., shorter wait time and less empty travel) because of increased vehicle availability.

Fleet operational costs are linked to fleet size and how the fleet is utilised. Operational strategies, such as relocation, routing, and passenger matching, directly affect how efficiently the fleet is utilised and the quality of service provided to users. This interplay creates the need to explicitly capture the interactions between service users and AT operations and to incorporate relocation-related factors (e.g., empty relocation distance) into cost estimation.

However, previous studies have often separately estimated AT fleet costs and optimised AT relocation operations. As a result, the relationship and trade-off between fleet operating costs and AT relocation performance are often overlooked. This study addresses this gap by explicitly modelling ATs, service users, and relocation operations, and integrating AT relocation operational factors to evaluate the fleet cost and operational performance. The evaluation is conducted using an agent-based simulation applied to the city of The Hague, the Netherlands.

The remainder of the paper is organised as follows. Section 2 reviews the literature. Section 3 presents model specifications. The application of the model to the case study city is described in Section 4. Simulation results are analysed in Section 5. Finally, Section 6 concludes and suggests directions for future research.

2. Literature review

Earlier studies focused on investigating the impacts of AVs on improving traffic capacity with reduced headways (Mahmassani, 2016;), and there has been significant interest in AV's potential to improve safety (Bagloee et al., 2016; Milakis et al., 2017). The capability of automated vehicle technologies to improve mobility accessibility and save energy through the integration of electric propulsion has also been investigated in recent years (Greenblatt and Shaheen, 2015; Shaheen and Bouzaghrane, 2019).

Given their great potential, there has been growing interest in exploring the impacts of different types of autonomous taxi services on urban passenger transport. The role of AT services in urban multimodal transport has been explored (Liang et al., 2016; Pinto et al., 2019; Shen et al., 2018). Liang et al. (2016) investigated the problem of introducing AT services to serve last-mile train trips. The service coverage and fleet sizes are optimised to maximise the operator's profit. Pinto et al. (2019) redesigned a transit network while considering AT services in low-demand areas. It is found that the optimised transit network, along with the determined fleet size of ATs, could improve service quality (e.g., users' waiting times).

The cost implications of AT services have also been investigated in different use cases. Burns et al. (2013) found that the cost of owning and operating an AT fleet to serve urban trips is low, and AT services could be cost-effective travel alternatives for taxis and private cars. Spieser et al. (2014) estimated the operating cost of AT services, indicating that AT services could be operated as a financially viable alternative to private cars. Bösch et al. (2018) provided a cost-based analysis of AT services in the presence of public transportation. Findings suggested that public transportation provided the most economically competitive service in urban contexts. The operating cost of AT services is lower than that of private cars and conventional taxis.

There are operational uncertainties and external costs that are introduced in urban AT systems. With fully controlled functions, AT operations could be managed to provide optimised services for its users. Hyland and Mahmassani (2018) presented optimisation-based AT-user assignment strategies. The study showed that the optimised assignment strategies could improve service quality in terms of waiting time while reducing the empty VKT. K. Zhang and Nie (2018) addressed the inefficiency associated with selfish routing by controlling a fraction of the automated AT fleet. The findings suggest that controlling a small proportion of vehicles with automated driving systems could bring the system very close to its optimal state. Levin (2017) investigated the system's optimal routing of ATs while considering congestion. The finding suggested that optimal routing methods could optimise their routes and avoid congestion.

In relation to AT relocation, the study by Chen and Kockelman (2016) showed that pricing policies could incentivise the use of ATs in areas with a surplus of vehicles, which could help balance vehicle availability across different areas. Operator-based relocation allows for identifying origin and destination zones, explicitly modelling the redistribution of vehicles from areas with high to low vehicle availability. Fagnant and Kockelman (2014) demonstrated the effectiveness of operator-based relocation strategies under different sizes of relocation locations and priorities of moving vehicles to adjacent sites in a grid-based urban area. The findings suggested that relocation operations could reduce waiting times for passengers. R. Zhang and Pavone (2016) proposed an optimal relocation policy to redistribute a minimal number of idle ATs while maintaining a balanced vehicle availability in an AT network. They demonstrated the effectiveness of the relocation policy in a case study, finding that all current taxi demand could be served using a controlled AT fleet that was only 70% the size of the current taxi fleet. Alonso-Mora et al. (2017) presented a modelling framework for real-time vehicle assignment and routing that includes the relocation of idling vehicles to high-demand areas, suggesting that the relocation operation could increase the service rates of travellers. Rossi et al. (2018) proposed a congestion-aware algorithm for routing and relocating AT that considers traffic conditions and the impact of vehicle relocation on network congestion. They found that congestion-aware relocation algorithms could improve waiting and travel times while avoiding additional congestion during vehicle relocation. Hörl et al. (2019) tested and compared different vehicle assignment and relocation strategies from the literature using MATSim. The study found that applying assignment and relocation policies could improve the waiting times of users, and the cost of AT service was predicted to be cheaper than private cars. Winter et al. (2021) investigated different strategies for redistributing idle ATs while considering parking locations and capacities. Their results suggested that vehicle relocation could reduce waiting times, decrease the fleet size and improve the equity of AT services. Dandl et al. (2019) investigated the impact of demand forecast aggregation on fleet operational performance with relocation. The findings suggested that relocation operations could be performed more effectively to improve the waiting times of users in the case of forecasting travel demand at a more disaggregated level.

Investigating the fleet cost and operational impacts of relocation requires integrating dynamic AT-to-passenger matching and routing functions. Relocation operations influence not only the quality of service provided to users but also the associated fleet operating costs. Therefore, we integrate dynamic AT–passenger matching and routing with relocation operations and incorporate operational factors to evaluate the trade-off between operational costs and fleet services, which is an aspect not addressed in prior work.

We therefore contribute to an agent-based simulation of the AT relocation operations to evaluate the trade-off between cost and operational performance. The agent-based model is developed to represent individual travel requests and AT operations with uncertainties, including AT-to-customer matching and AT routing. A demand generator creates time-dependent requests across the service areas and integrates with the passenger matching component to optimally assign ATs to users.

Furthermore, operator-based relocation mechanisms are designed to mitigate the imbalance between the expected demand and supply of ATs. The relocation function component is linked with the demand generator and routing component, aiming to test the effectiveness of relocation strategies. The relocation origin and destination points are identified, and the redistribution of vehicles from areas with high to low vehicle availability is explicitly modelled.

With the flexible modular design, a traffic component based on the node and link movement rules is incorporated into the simulation, which can account for congestion affecting both in-service vehicles (carrying users) and relocation vehicles. A fleet cost structure for AT services that is defined as a function of total distance travelled, served users, and fleet size (i.e., the number of ATs) is included to evaluate the cost impact under a relocation strategy.

We employ a scenario-based approach that sets out future scenarios with multiple operators, each of which performs its operations to transport its users in the shared environment. This allows us to investigate real-world urban mobility markets where multiple AT services operate simultaneously in the same geographic area. As a case study, we apply the functional components to the city of The Hague, the Netherlands, to evaluate the cost and operational performance in terms of service quality.

3. The model

3.1. Model overview

Agent-based modelling describes a system at the level of its constituent units (Bonabeau, 2002; Macal and North, 2015). In this approach, a system is represented as a collection of agents, and the interaction between agents can be realistically captured. Agent-based modelling also allows flexible changes to model components and simulation settings through modular design. The system under investigation can be described at different levels (e.g., individual vehicles and aggregate travel conditions, individual users and aggregate demand), making it well-suited to studying AT systems.

The modelling framework includes five core functional components: a demand generator, an optimal assignment component, a vehicle relocation component, a mesoscopic traffic simulation model, and the time-dependent shortest route calculation component (Fig. 1). Individual travel requests for an AT operator are generated with departure time, origin and destination based on the existing travel demand data. The

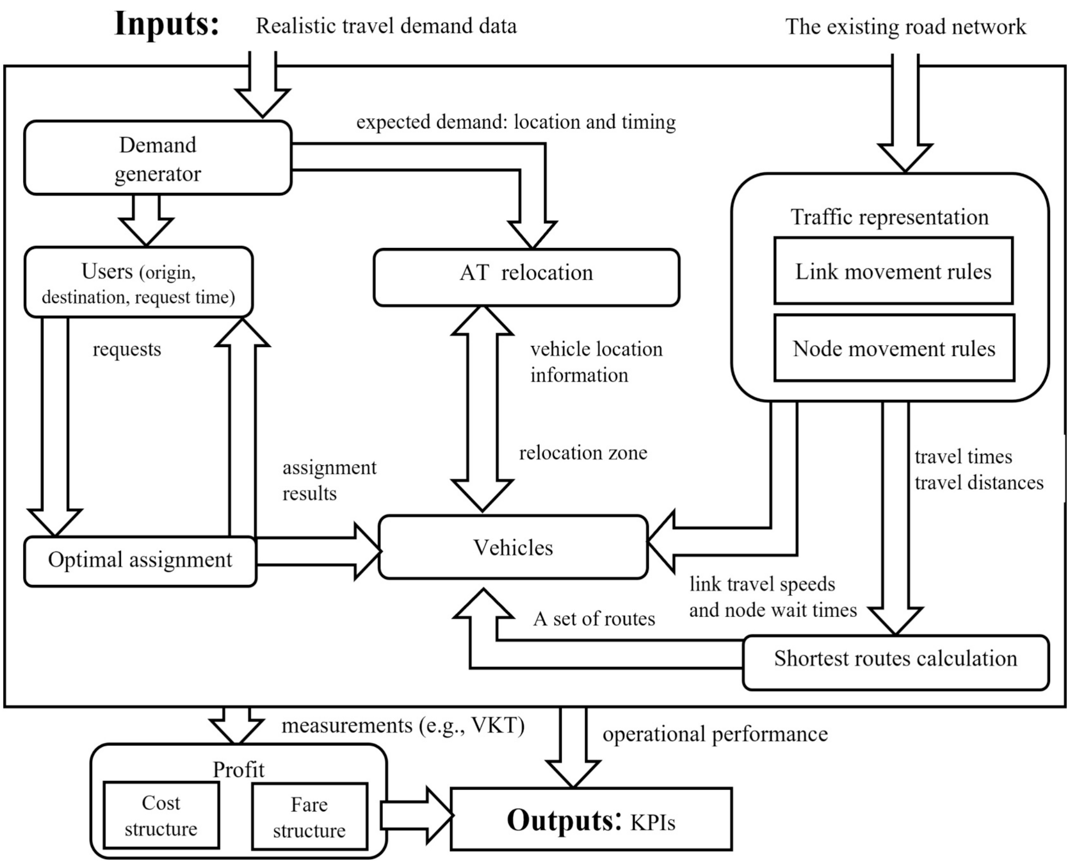

Fig. 1. Overview of the model architecture.

demand generator also provides an estimate of the expected number of travel requests. The optimal assignment component is responsible for matching available vehicles operated by an operator with its users. Link and node movement rules are incorporated to capture traffic dynamics. Through the node and link mechanisms, the model reproduces road travel conditions and estimates the travel times of vehicles across the road network. The routing component then identifies time-dependent shortest routes between locations for each vehicle in moments: before picking up a user, at the beginning of transporting a user to their destination, and before relocating to areas with a shortage of vehicles.

The operating costs for AT fleets are derived using the simulation outputs (e.g., empty and occupied VKT, number of served trips, and fleet size). Profit is also estimated using fare structures and operating costs, allowing for investigating trade-offs between fleet costs and relocation operational performance.

3.2. Vehicle assignment, routing, and traffic components

An optimal vehicle-to-passenger assignment component is developed to match available vehicles to grouped requests from users. This is done through pre-assignment by searching the nearest available vehicles for requests and prioritising earlier requests. Vehicle-to-request pairs are generated by assigning the nearest available vehicles. For each request r_i in set $R = \{r_0, r_1, \cdots, r_n\}$, the nearest vehicles v_i in the Vehicle set $V = \{v_0, v_1, \cdots, v_n\}$ could be reassigned to any other request in the Request set R (see Fig. 2). An optimal assignment can be obtained if it minimizes the sum of the cost of every assignment pair (e.g., travel distances). A bipartite graph is constructed whose vertices are two independent sets (i.e., set V and set R) (see Fig. 3). The bipartite graph is represented by an adjacency matrix in which the horizontal row stands for vehicles in the set V and vertical columns for requests in the set R. The assignment problem is solved using the Hungarian method implemented in the work by Wang et al. (2022).

Traffic conditions are considered by incorporating a mesoscopic traffic simulation model that is widely used for estimating urban network travel time at an aggregate level with tracked vehicles (Chiu et al., 2011; Mahmassani, 2001). A set of vehicle movement rules is defined to govern the movement of vehicles. Briefly, in the link (road segment) movement, vehicles (e.g., in-service vehicles and relocation vehicles) experience a speed calculated by a macroscopic speed-density relationship. Travel speeds can be calculated based on the established relationship between speed and density. When the density d is less than the critical density d_c, the speed V can be calculated using Equation 1: $V = v_0\left(1 - \frac{d}{d_j}\right)$. Where v_0 is the maximum speed respecting the urban speed limit, and d_j is the jam density. When the density d exceeds the critical density d_c, the speed is calculated using Equation 2: $V = v_0 d_c\left(\frac{1}{d} - \frac{1}{d_j}\right)$. In modelling the movement of in-service and relocation vehicles, vehicles are stacked at accumulation areas (assumed places at nodes) for being transferred from an upstream road segment to a downstream road segment. The routing component is responsible for computing the time-dependent shortest routes between any two given points using the Dijkstra algorithm. For private car travel, the routing component computes time-dependent shortest paths between their origin–destination pairs of unserved trips using the Dijkstra algorithm, in the same way as for AT vehicles. As a result, the reported congestion and travel-time effects reflect interactions between in-service AT vehicles, relocation AT vehicles and private car traffic arising from unmet AT demand.

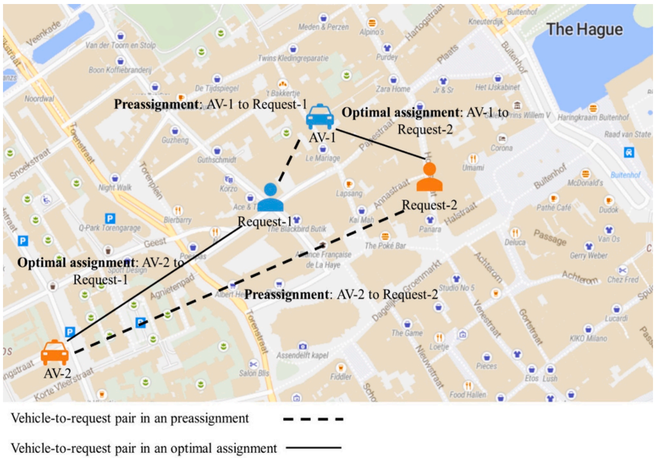

Fig. 2. A real-world scenario for potential benefits of grouping requests.

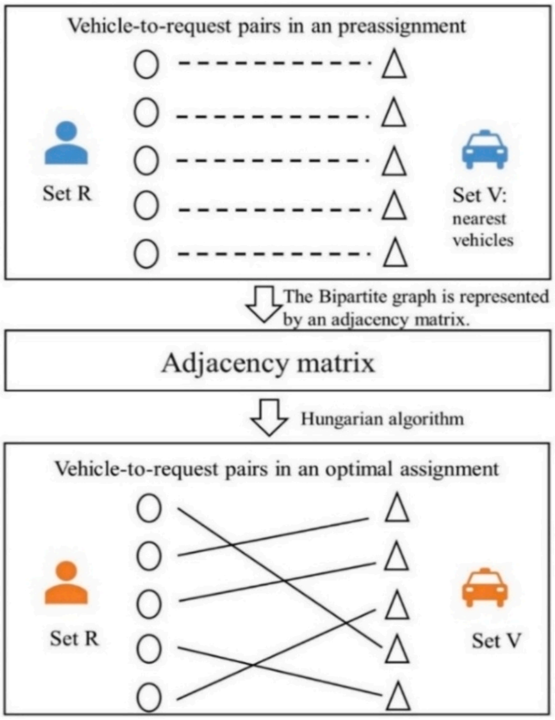

Fig. 3. Schematic diagram for the vehicle-to-passenger assignment.

3.3. Fleet cost and fare structure

The total fleet cost is an important financial performance indicator that can be used to evaluate profitability. In urban AT fleets, the operational cost is influenced by the total distance travelled by the fleet (d_{fleet}), the number of served trips (n_{trips}) and the fleet size (n_{fleet}) (Hörl et al., 2021). We incorporate the cost model in Eq. (3) to estimate the operating cost of urban AT fleets that provide door-to-door service to single users.

$$C = c_d d_{fleet} + c_t n_{trips} + c_f n_{fleet} \tag{3}$$

where,

c_d is the cost per vehicle kilometre (including both trips with users and trips without users, such as pickup trips and relocation trips).
c_t is the cost per trip.
c_f is the cost per vehicle.

The fare is the out-of-pocket cost paid by a user. There are uncertainties associated with estimating fares for single-use AT services. We base the AT fare on the mobility-on-demand model, using UberX as a reference point (Oh et al., 2020). While aligning with the fare structure in the real world, the single-ride fare p is structured by a base fare, a distance-based fare f_d and a time-based fare f_t.

$$p_{dt} = \eta(f + f_d d + f_t t) \tag{4}$$

where,

η is the saving factor for AT services relative to an existing mobility-on-demand service.
f is the base fare used in mobility-on-demand services.
d is the travel distance with a user.
t is the travel time with a user.

In Eq. (4), incorporating a time-based fare component $f_t t$ means that as travel times increase, such as in congested networks, the fare also increases. To examine how this time component affects operator profits, we also test a distance-only fare structure (see Eq. (5)) for comparison analysis.

$$p_d = \eta(f + f_d d) \tag{5}$$

In the time-based fare structure (see Eq. (4)), the fare paid by a user p_{dt} consists of a base fare f, a distance-based component $f_d d$, and a time-based component $f_t t$ proportional to in-vehicle travel time. In contrast, the distance-based fare structure in Eq. (5) defines the fare p_d using only the base fare f and the distance-based component $f_d d$, and excludes any time-based charging. All fare expressions represent positive monetary costs paid by AT service users.

3.4. Autonomous taxi relocation

3.4.1. Basic definitions and relocation procedures

A relocation mechanism is developed to redistribute available vehicles (idle and not assigned to serve users) among locations in anticipation of future requests. An urban service area was divided into traffic analysis zones (TAZ). All TAZs, which correspond to origins and destinations, are potential relocation zones. Expected demand is estimated using historical data in an O-D matrix and a 15-minute departure time distribution. The total number of trips between every pair of TAZs throughout the study period (i.e., the morning peak hours) is specified in the O-D matrix. We can calculate the number of trip requests for every time interval using a fraction of the trips during that time interval.

To tackle the imbalance between available vehicles and expected demand, we classify relocation zones into two types: *Supplier zones* and *Demander zones*. In Supplier zones, available vehicles exceed expected demand; in Demander zones, a vehicle shortage is anticipated.

3.4.2. AT relocation mechanism

Relocation operations, controlled by the system operator, are scheduled on a cyclical basis. The relocation time interval for performing relocation operations is predetermined. At the start of each relocation time interval, Supplier and Demander zones are identified by comparing the number of available vehicles and the number of expected requests. Vehicles from the Supplier zones are relocated to the Demander zones. The specific relocation procedures (for an operator) are described below:

(a) The number of available vehicles and the number of expected requests in each zone are determined at the beginning of the relocation time interval.
(b) Relocation indices that are indexed to changes in the available vehicles and future demand (i.e., 15 min) in zones are calculated. Similar approaches to this step have been used in AT relocation in a grided city or relocation in carsharing systems (Fagnant and Kockelman, 2014; Balac et al., 2019). At each decision moment, relocation indices for all zones are computed using Eq. (6).

$$R_i = V_t(V_{ti}/V_t - R_{ti}/R_t) \tag{6}$$

- R_i is the relocation index for the zone i.
- V_t is the total number of available vehicles of an operator in the service area. The service area is comprised of a group of zones $\{z_1, \cdots, z_I\}$ and use the index $i \in \kappa = \{1, \cdots, I\}$ to refer to zone i.
- V_{ti} is the number of available vehicles of an operator in zone i, $i \in \kappa$.
- R_t is the total number of expected requests for an operator' service in the service area.
- R_{ti} is the number of expected requests for an operator's service in the zone i.

(c) Based on by the relocation index, zones with positive R_i values indicate a surplus of available vehicles and are classified as *Supplier zones*, whereas zones with negative R_i values indicate a shortage of available vehicles and are classified as *Demander zones*.
(d) The vehicles in a Supplier zone will be relocated to the closest Demander zone. The number of vehicles for relocation in each zone is the additional number of available vehicles (those not needed to serve expected demand in the Supplier zone).
(e) The time-dependent shortest routes between the Supplier and Demander zones are computed using the Dijkstra algorithm for every relocation vehicle.

In AT relocations, relocation movements occur between Supplier and Demander zones. The relocation vehicles and the distance travelled from identified Supplier zones to identified Demander zones are tracked.

4. Model application

The simulation model was developed in the Anylogic platform using Java programming language. The ABM is populated with existing travel demand data and road network data from the case-study city of The Hague in the Netherlands.

4.1. The road network and urban service area

The model contains a realistic representation of the road network and service area in the case study city. The road network that we have used covers the main districts around the city of The Hague. Road attributes are initialised based on the existing traffic data. The road attributes, including capacity, speed at capacity, free-flow speed, and jam density, are initialised based on the traffic data exported from OmniTRANS, a multimodal transport planning software package. The speed–density parameters for different urban road types are adopted from Wang (2023), as detailed in Appendix B of that study. Critical densities are derived based on the corresponding capacity flows and speeds at capacity associated with each urban road type.

We preprocess the geospatial data and use it as input to the model (see Table 1). 49 TAZs frame the urban service area. The locations of centroids of the TAZs are used as the points of travel requests injection in the road network; they are designated as users' origin and destination as well as service points for AT services.

4.2. Travel demand data

Individual users are created to simulate the behaviour of requesting AT services. 27,452 private care trips occur within the urban service area of The Hague. The temporal pattern of travel demand is shown every 15 min in the morning peak period from 5:30 am to 10:00 am in Fig. 4. The demand generator generates time-dependent travel requests using departure time fractions and an OD matrix data specifying demand between TAZs. Travel requests should be generated and characterised by

Table 1
A Summary of the Model Parameters for the Baseline Scenario.

Parameter/characteristics	Value
Travel demand (Z)	25,800 interzonal trips
Centroids (denoted by s)	49
The number of fleet operators i	3
Time steps for speed update	6 s
Vehicle assignment Time interval Δt	15 s
The search distance for vehicle assignment	5000 m
Vehicle seat capacity	1 person
The average number of vehicles at the beginning of the simulation $(N_0 : n_{o_1} = n_{o_2} = n_{o_3} = \frac{N_0}{3})$	N_0: 51 vehicles per service point
η saving factor for AT services relative to an existing MoD service	0.6
Cost per vehicle kilometer c_d	0.095 euro per VKT
Cost per trip c_t	0.364 euro
Cost per vehicle c_f	7.857 euro
Base fare f	1.4 euro
distance-based fare f_d	1.2 euro per km
Time-based fare f_t	0.26 euro per min
Vehicle increment Δg per service point for sensitivity analysis	5 vehicles
Relocation interval	15 min

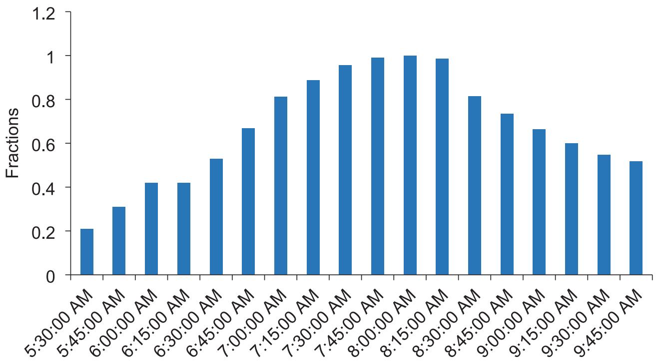

Fig. 4. Departure time fractions per 15 min of OD matrix.

their origin, destination, request time, and the identification of an operator that they are willing to use. OD demand derived from private car trips is used as a proxy for potential AT demand, and all trips initially request AT services. When ATs are unavailable, travellers remain unserved, following the modelling approach adopted in Wang et al. (2022). These unserved trips are assumed to be completed by private cars and are explicitly included in the mesoscopic traffic simulation as background traffic.

4.3. AT service configurations

Regarding fleet deployment, we define N as the average number of vehicles deployed for all operators in each service point of the model. We denote the average fleet size of each operator at each service point as n_{o_i} where $\sum_{i\in\{1,2,3\}} n_{o_i} = N$. The Fleet n_{o_i} is proportionally distributed as a function of demand for an operator's service in each service point. The fleet size n_{o_i} for AT operator o_i is treated as a parameter for which the simulation is repeated for various values. We analyse the impact of varying fleet sizes on the operational and financial performance of AT operators by initially simulating a small fleet size and gradually increasing it to larger sizes. We initiate the fleet sizes in the baseline scenarios as $n_{o_1} = n_{o_2} = n_{o_3} = \frac{N_0}{3}(N_0 = 51)$. N_0 is set to smaller values to explore the scenarios where an operator brings more vehicles to the service area.

z_{o_i} will be used to denote the demand for operator o_i and Z as the total demand (27,452 trips) in the city for the AT services, thus $\sum_{i\in\{1,2,3\}} z_{o_i} = Z$. We model the 25,800 interzonal trips. Regarding the vehicle types used in this study, carmakers (Renault UK, Toyota) are producing and marketing small driving pods that take up less road and parking space. Moreover, small-sized vehicles can save more energy with reduced weight. Hence, we assume that ATs are small single-occupancy vehicles that could be ready for the market soon. We are using the UberX fare structure that is active in the Netherlands. We have $\eta = 0.6$ (60% of the existing MoD).$f = 1.4\,\text{euro}$, $f_d = 1.2\,\text{euro per km}$, $f_t = 0.26\,\text{euro per min}$ in Eq. (5).

The cost model in Eq. (3) is parameterised using predicted values for single occupancy AT services. Using a conversion rate of 0.97 euro/CHF, the cost parameters reported by Hörl et al. (2021) are converted and adopted for this case study. The distance-based operating cost is specified as $c_d = 0.095$ euro per vehicle-kilometre. Within the cost model, the parameter c_t represents a trip-based cost, which is set to $c_t = 0.364$ euro per trip. The fixed cost associated with each vehicle used during morning peak is set $c_f \approx 7.857$ euro. The distance-based vehicle operating cost (c_d) captures operating costs associated with AT usage. This parameter is distinct from the distance-based and time-based fare components charged to users. Table 2 summarises the model parameters and case study characteristics for the baseline scenario.

Operator 2 and operator 3 are set with the same operational parameters, and both represent scenarios without relocation. We included three operators to reflect the typical real-world situation where multiple operators coexist within a shared market. A scenario framework with three operators is more representative of multi-actor environments and serves as parallel baselines that facilitate structured comparisons between the relocation case (Operator 1) and non-relocation cases (Operators 2 and 3). Simulation results are analysed and compared across three operators, providing clearer reference points when comparing against the relocation case. It also ensures that the effects are consistently evaluated through defined indicators, as they operate simultaneously in a shared road network.

5. Simulation results and analysis

Simulation is performed to explore the implications of AT systems with multiple operators. A set of performance indicators is defined to reflect the different aspects of system performance. The main performance indicator is summarised in Table 2 and described in detail. Each scenario was evaluated using 10 independent simulation runs with different random seeds. The reported KPI values represent the average

Table 2
Key performance indicators for performance assessment.

Indicator	Explanation
Waiting time	out-of-vehicle time a user spends waiting for the assigned vehicle to reach the pickup location.
Travel time	the time a user spends in a vehicle moving from the origin location to the destination location.
Unserved trips	the trips of users that the AT operator cannot find available to serve users.
Total VKT	total VKT is measured by multiplying the total number of vehicular trips by the length of these trips, including the empty distance travelled.
Empty trips	unoccupied pickup trips (without passengers inside a car).
Empty VKT	empty VKT is the total pickup distance travelled by unoccupied vehicles. It is calculated by multiplying the total number of empty trips for pickups by the lengths of these trips.
Vehicle utilization	the average number of trips served per vehicle in the simulation time
Relocation trips	relocation trips are vehicular trips made by relocation vehicles.
Relocation VKT	calculated by multiplying relocation trips by the distance travelled by relocation vehicles.
Fleet profit 1	total revenue from distance-based fares minus the total operating costs.
Fleet profit 2	total revenue from distance- and time-based fares minus the total operating costs.

results across the simulation replications.

We design simulation experiments to examine relocation impacts on costs and operational performance in Section 5.1. The impacts of increasing fleet sizes are examined in Section 5.2.

5.1. Simulation scenarios for operator-based relocation operations

Relocation operations for an operator are modelled for comparison. It is assumed that all operators have the same demand shares and AT fleet sizes. The simulation experiments examine how relocation operations affect the operators' performance in a competitive AT market with multiple AT operators. We compare the system performance of operator 1, which performs relocations, against the other operators (operators 2 and 3), which do not perform relocations.

The simulation results in Table 3 show that the relocation performed by Operator 1 reduces the average travel times by 1 min as compared to Operators 2 and 3. Relocation operations by Operator 1 also improve waiting times by approximately 11% compared to the competing operators. The reason is that vehicles are proactively moved to high-demand areas and subsequently become available for incoming requests with shortened pickup distances. It is shown that there is a significant reduction in the empty VKT (the total pickup distance covered by vehicles) of Operator 1 compared to the empty VKT generated by Operator 2 or Operator 3.

Moreover, Table 3 reveals that Operator 1 has a high percentage of served trips, meaning that more passengers are transported by Operator 1, which performs relocation operations. That means relocating vehicles can mitigate the imbalances between available vehicles and future requests: Vehicles are relocated from zones with surplus capacity to the zones with a vehicle shortage, allowing the vehicle-to-passenger matching component to allocate available vehicles to incoming requests. As a result, Operator 1′s profit can increase by up to 16% compared to competitors that do not employ relocations. While relocation does generate additional VKT, single-occupancy autonomous taxis incur relatively low operating costs, resulting in just a modest increase of 300 euros in operating expenses alongside a gain of more than 2,000 euros in additional profit.

Although vehicle relocations can shorten waiting times and serve more trips at higher profit, they also generate additional VKT. The relocation of VKT has the potential to add more road traffic. To have a closer look at the relocation operations, Fig. 5 demonstrates the vehicles in relocations over the morning hours (we are studying). Relocations occur in the very early morning and late morning hours. No relocation occurs in the busiest time interval ([7:30 am, 11:00 am]) when nearly all vehicles are actively serving users. This is because the AT vehicle utilisation, measured as the number of trips served per vehicle during the morning period, is high for the autonomous taxi fleet, and no idle vehicles are available for relocation. The additional empty relocation VKT and the VKT in serving more demand are generated in very early morning hours ([5:30 am, 7:30 am]) and late morning hours ([11:00 am, 12:00 pm]) when roads are relatively less congested (the highest demand arises after 7:30 a.m. in Fig. 4).

Table 3
Key performance indicators with relocation operations of operator 1.

Fleet operator	o_1	o_2	o_3
Relocation operation	Yes	No	No
Avg. waiting time (minute)	7.55	8.57	8.63
Avg. travel time (minute)	20.48	20.66	20.68
Total VKT (km)	39,497	37,679	37,660
Empty VKT (km) (pickup trips)	8318	9482	9527
Empty VKT (km) (relocation trips)	1745	0	0
The percentage of empty VKT of the total VKT	25.47%	25.16%	25.30%
Vehicle utilisation (trips per car) in the morning hours	7.64	7.33	7.31
Served trips	6367	6106	6093
Operating costs (Euro)	12,615	12,347	12,340
Fleet profit 1 (Euro)	15,182	13,084	13,034
Fleet profit 2 (Euro)	35,519	32,761	32,692

Fig. 6 illustrates the number of active vehicles (i.e., vehicles assigned to pick up customers or performing relocation operations), showing that relocation operations bring more vehicles to the roads, mainly in off-peak periods (either in the very early morning hours or late morning). Hence, relocating vehicles to a more advantageous position in anticipation of future demand does not cause more traffic congestion. Relocating vehicles instead alleviates demand–supply mismatches, leading to shorter waiting times, more served trips, and a higher profit.

In Fig. 7(a), the map highlights zones (Demander zone) experiencing vehicle shortages and zones (Supplier zone) with surplus vehicles. The red bar represents the vehicle shortage in a Demander zone, while the blue bar represents the vehicle surplus in Supplier zones. Demand (requests) is represented at the centroids of TAZs. As expected, vehicle shortages occur in areas with high number of morning commuters. For example, there are not enough available vehicles to serve the demand in a Demand zone (ZoneID 107). Simulation results show a total shortage of 160 vehicles in the morning hours ([5:30 am, 12:00 am]) in this Demander zone (see Appendix). Conversely, low-demand zones (e.g., zoneID 87 and zoneID 86) have a lower number of morning commuting requests, about 298 and 513 requests, respectively. ATs in these zones can be relocated to high-demand zones to transport more morning commuters. Interestingly, some high-demand zones like zone 89 have a high number of 1310 morning commuters for AT services. However, there are still available vehicles (21 vehicles) at a specific time for relocations (e.g., 06:33 am in Appendix A). This is because these zones are also destinations where ATs drop off their users. Time-dependent requests are generated at a high spatial and temporal resolution and anticipate travel demand at 15-minute intervals. On short notice, vehicles can be relocated to serve more demand at other zones to improve profits and vehicle utilisation rates.

The relocation vehicle flow (see Fig. 7(b)) visualises how operator 1 proactively redistributes AT from Supplier zones to meet demand in Demander zones. The arrows show the relocation direction, and the width is indexed to the number of relocation vehicles. Simulation results show that AT operators relocate idle ATs from multiple Supplier zones to mitigate the vehicle shortage in a targeted Demander zone. That is because, in the early hours ([6:00 am, 7:30 am]), users commute from home to work locations, and then the number of requests for AT services increases. Few vehicles are available to perform relocation operations to meet the anticipated commuting demand. Moreover, we found that the relocation distance between the Demander zone and Supplier zones is as long as the relocation from zones that are far away in the city. As a result, the relocation could generate a large percentage of empty VKT. Although additional VKT could lead to a higher operating cost, the AT operating cost is lower because of the elimination of paid drivers. Also, we consider a smaller single-passenger AT, further reducing operating costs. Therefore, applying relocation operations in AT systems is cost-effective and can serve as a strategy to improve service quality and generate higher profits in the modelled morning peak scenarios. Thus, morning commuters could benefit from the convenience of on-demand services and the high-quality services they provide.

5.2. Simulation scenarios for evaluating changes in fleet sizes of an operator

This section evaluates the scenarios in which an operator (e.g., operator 1) increases its AT fleet to improve the service offered to the users. The cost impacts of fleet sizes and fleet performance (e.g., trips served per car) are investigated for all operators o_i ($i = 1,2,3$). Table 4 presents the simulation results for the baseline scenario where the fleet is equal all operators ($n_{o_1} = n_{o_2} = n_{o_2}$). We then explore two scenarios in which the number of vehicles allocated to operator 1 increases by Δg (scenario one: 5 vehicles or about 30% increase in the fleet size of operator 1) and $2{*}\Delta g$ (scenario two:10 vehicles or about 60% increase in

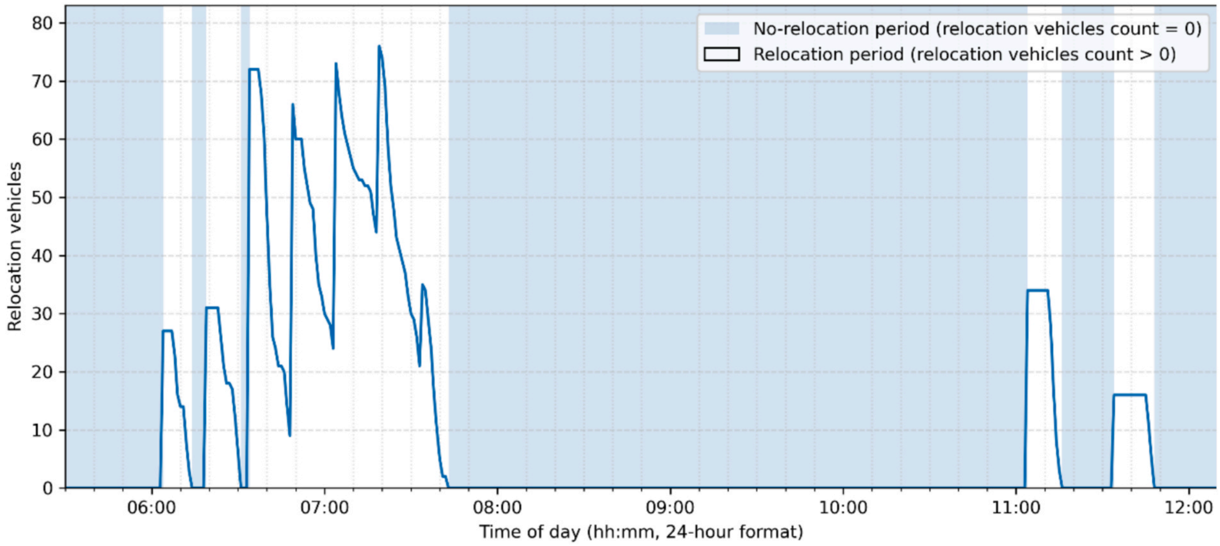

Fig. 5. The number of vehicles in relocation over time.

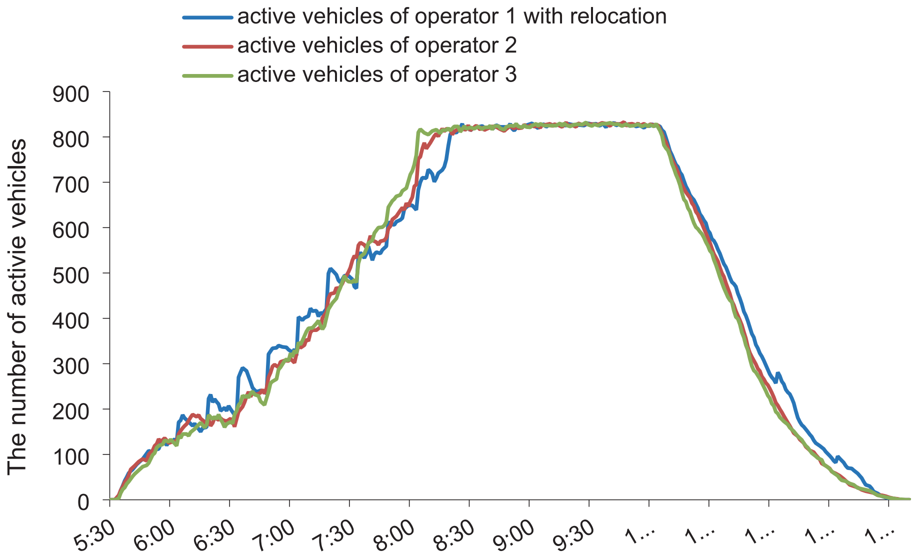

Fig. 6. The number of active vehicles for operators over time (hh:mm, 24-hour format).

the fleet size of operator 1).

The simulation results in Table 5 indicate that an increased fleet size could improve the service quality provided by operator 1 as measured by average waiting time, compared with the other operators. Moreover, as expected, fewer empty VKT are generated in the system managed by operator 1; as the fleet size increases, the empty VKT reduces from 25.45% of the total VKT in the baseline scenario to 20.35% of the total VKT in the scenario, where 10 additional vehicles are added per service point.

A larger fleet decreases vehicle utilisation. Results indicate that vehicle utilisation measured by the number of trips per car decreases from 7.32 to 5.63 as the fleet size increases. Currently, commuters using private vehicles in our case study city may take 20–30 min to complete one trip. Private vehicles remain parked for up to 90% of the time. Although vehicle utilisation of AT operators is reduced, they attain much higher usage rates compared to private vehicle use.

Furthermore, the simulation results in Fig. 8 show that increasing in the fleet size of operator 1 can improve the percentage of served trips over time. The percentage of served trips for operator 1 is significantly higher than in the baseline scenario and for the other competing operators (who do not add vehicles), particularly when travel request volume is high. This means that more users of operator 1 are being transported, especially around peak hours. In this regard, a larger fleet can help an operator to serve more users and improve the service quality offered to them.

However, the simulation results in Table 5 show increases in the average waiting times of the other fleet operators (o_2 and o_3) and the average travel time for all operators. For example, the average travel time increases from 20 min to 24 min. The reason is that increasing the fleet size of operator 1 leads to more requests being served on the road network; operator 1 brings more vehicles to the roads (see Fig. 9(b)). Fig. 9(a) shows the total number of active vehicles operated by three operators across the road network has increased. More vehicles circulating across the road network causes more traffic congestion, leading to average travel times increasing by up to 4 min. This means that in the multiple-operator AT system, the growth of the fleet size of an operator brings an adverse effect on the road travel conditions, thereby degrading the service quality of its competitors.

The main finding is that an operator may be motivated to increase its fleet size to obtain a higher profit in the competitive mobility market. In

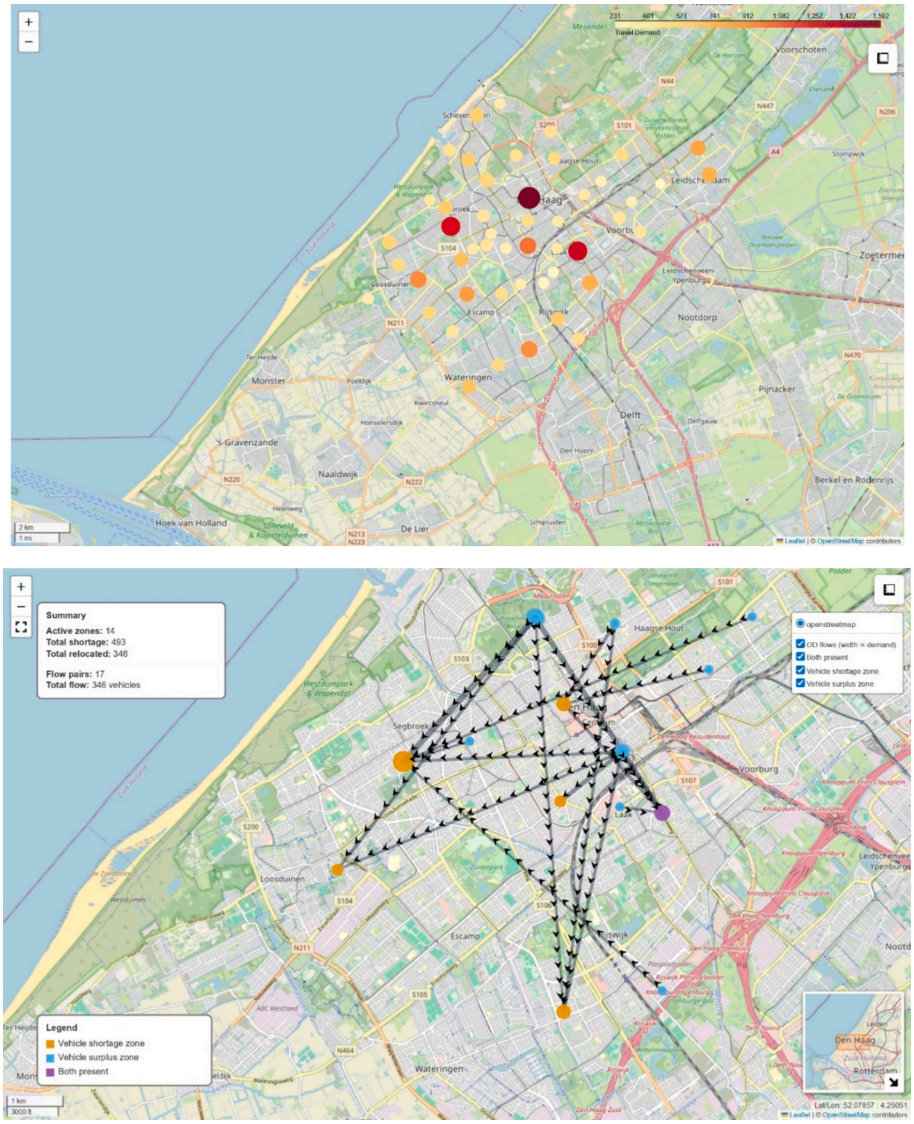

Fig. 7. Map of relocation vehicles, Supplier zones, and Demander zones. (a) travel demand over the study area. (b). Relocation Flow between the Demander zone and Supplier zone.

Table 4
Key performance indicators in the baseline scenario where the fleet is distributed equally.

Fleet operator	o_1	o_2	o_3
Fleet size	$n_{o_1}=n_{o_2}=n_{o_3}$ (where n_{o_i} represents the number of vehicles operated by operator o_i)		
Avg. waiting time (minute)	9.09	9.06	9.11
Avg. travel time (minute)	20.30	20.58	20.60
Total VKT (km)	37,906	38,074	37,317
Empty VKT (km)	9646	9792	9429
The percentage of empty VKT of the total VKT	25.45%	25.72%	25.27%
Vehicle utilisation (trips per car)	7.32	7.30	7.24

addition to the increased profit, the growth of the fleet size of an operator leads to improvements in the average waiting times of its users. However, it comes at the cost of its competitors' operational efficiency, as measured by average travel times and waiting times. This is because increasing fleet size to serve more trips brings more vehicles to the roads, adding to traffic congestion.

5.3. *Sensitivity analysis of relocation and cost parameters*

The sensitivity analysis quantifies the trade-off between operational cost and service quality across relocation intervals of 0, 5, 15, 25, and 35 min in Fig. 10. Compared to the no-relocation baseline, the shortest interval (i.e., 5 min) produces the most significant increase in relocation empty distance (18.1%). This impact decreases steadily with longer intervals, reaching 5.4% at 35 min. Moreover, we find that the total vehicle operating cost changes only marginally, from 7.6% at 5 min to 6.5% at 35 min. This stability reflects that even without relocation, a large proportion of empty vehicle-kilometres is already incurred for passenger pickups in an on-demand automated taxi system. Proactive relocation replaces some of the reactive empty movements of AV towards anticipated demand locations, which improves waiting times and enables more trips to be served.

In terms of service quality, the 5-minute interval delivers the greatest improvements, with a 1.7% increase in served trip rate and a substantial 16.2% reduction in average passenger waiting time. These gains diminish as relocation becomes less frequent, falling to 0.3% in the served trip rate and around 4.0% in waiting time at 35 min. Overall, short relocation intervals significantly enhance customer experience but at a slightly higher operational cost, whereas longer intervals reduce

Table 5
Key performance indicators with the increase in vehicle supply of operator 1.

	scenario one			*scenario two*		
	o_1	o_2	o_3	o_1	o_2	o_3
Fleet size (Δg or $2\Delta g$ represents vehicle increment per service point)	$\boldsymbol{n}_{o_1} + \boldsymbol{\Delta g}$	n_{o_2}	n_{o_3}	$\boldsymbol{n}_{o_1} + 2\boldsymbol{\Delta g}$	n_{o_2}	n_{o_3}
Avg. waiting time (minute)	8.72	9.50	9.45	9.13	9.73	9.52
Avg. travel time (minute)	21.80	21.35	21.85	24.54	24.18	24.21
Total VKT (km)	40,414	38,116	37,721	43,530	37,400	37,019
Empty VKT (km)	8931	9563	9463	8857	9440	9293
The percentage of empty VKT of the total VKT	22.10%	25.09%	25.09%	20.35%	25.24%	25.10%
Vehicle utilisation (trips per car)	6.34	7.45	7.36	5.63	7.36	7.31

costs but offer more modest service improvements. A balanced interval can therefore support both passenger satisfaction and sustainable fleet utilisation, providing a practical basis for designing relocation strategies that align with specific operational objectives and market conditions.

We test the sensitivity of cost per kilometre (c_d) travelled, and the c_d parameter is varied from the baseline of 0.095 €/VKT in 20% steps. As shown in Fig. 11, the ratios of operating cost to fare are presented for distance-based and time-based fare structures at different relocation intervals. The ratios increase almost linearly. The distance-based fare structures (see Eqs. (3) and (4)) exhibit a steeper increase than the time-based structure; when vehicle operating costs (e.g., energy or maintenance) rise, time-based fares sustain margins better with relocations, while distance-based margins wear down faster with higher operating costs.

Relocation interval primarily affects service outcomes such as waiting time and trips served; however, it is shown that differences in the operating cost-to-fare ratio across relocation intervals are small within each fare type. That means the relocation interval has little impact on the operating cost-to-fare ratio. This aligns with the limited variation in total operating cost increases in Fig. 10. It is therefore implied that the relocation interval can be chosen mainly based on service KPIs without charging the cost-to-fare balance in an on-demand automated taxi system. By contrast, the distance-based operating cost (c_d) parameter is the main driver that significantly influences the overall fleet operating costs.

6. Conclusions and future directions

6.1. General discussion and recommendations

Using the developed agent-based model, in which functional components for AT operations are linked, we evaluate the trade-offs incurred in vehicle locations while capturing the operational uncertainties, and we investigate how fleet sizes affect vehicle utilisation and service qualities provided to users. The discussion is based on results obtained from simulations of the morning peak period. The reported findings, therefore, reflect peak-hour AT operation.

Operators may increase the size of their vehicle fleet in the future to improve the service quality (e.g., waiting times) and serve more trips with a greater profit. However, larger fleet sizes result in more traffic on the road network and, therefore, deteriorate its competitors' service quality (average waiting and travel times). Policymakers (e.g., city authorities) should therefore regulate fleet sizes in competitive AT markets to avoid negative externalities (e.g., congestion and pollution) and ensure quality services to users.

Relocations can increase operational efficiency (more trips per vehicle) while improving user service quality. Because vehicles are proactively moved to high-demand areas, more trips are served, and profits increase. The operating costs per vehicle kilometre are comparatively low for single-passenger AT services. This is primarily due to the elimination of the high cost of staff salaries and staff relocation rides in carsharing systems. In contrast, operator-based relocations in competitive AT systems show higher profit than in competitive carsharing systems, where an unprofitable situation is estimated (Balac et al., 2019). Our findings highlight the positive effect of operator-based relocations on both service and profit, supporting the development of relocation capabilities in AT management systems.

We also found that fare structures can significantly influence the profit of an operator. When congestion occurs during peak hours, distance- and time-based fare structures can help companies achieve a higher profit. Operators should carefully consider the fare structure to

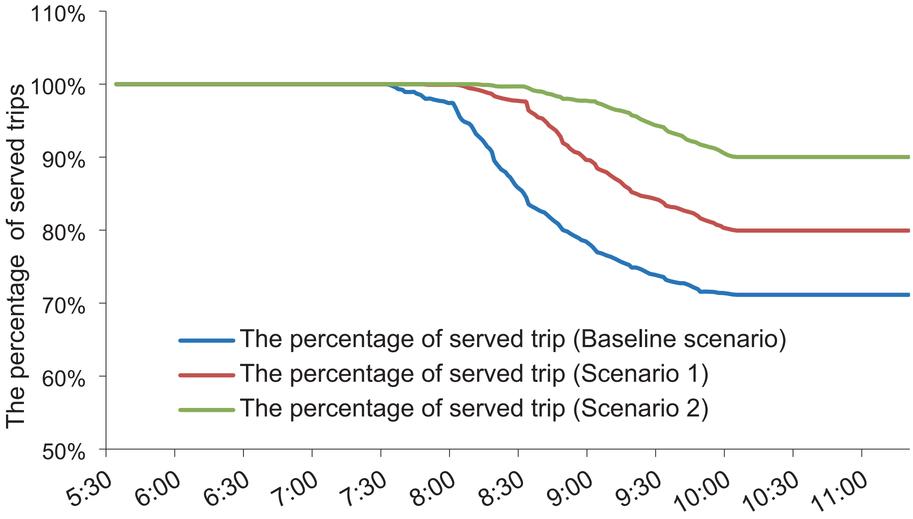

Fig. 8. The percentage of served trips for AT operator 1 over time (hh: mm, 24-hour format).

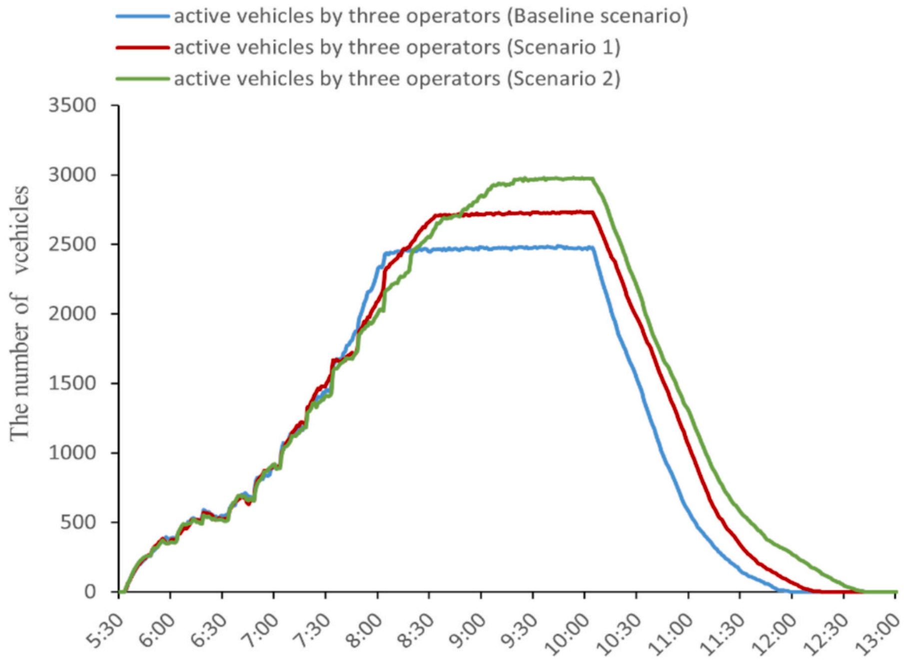

Fig. 9a. Active vehicles by all three operators over time(hh:mm, 24-hour format).

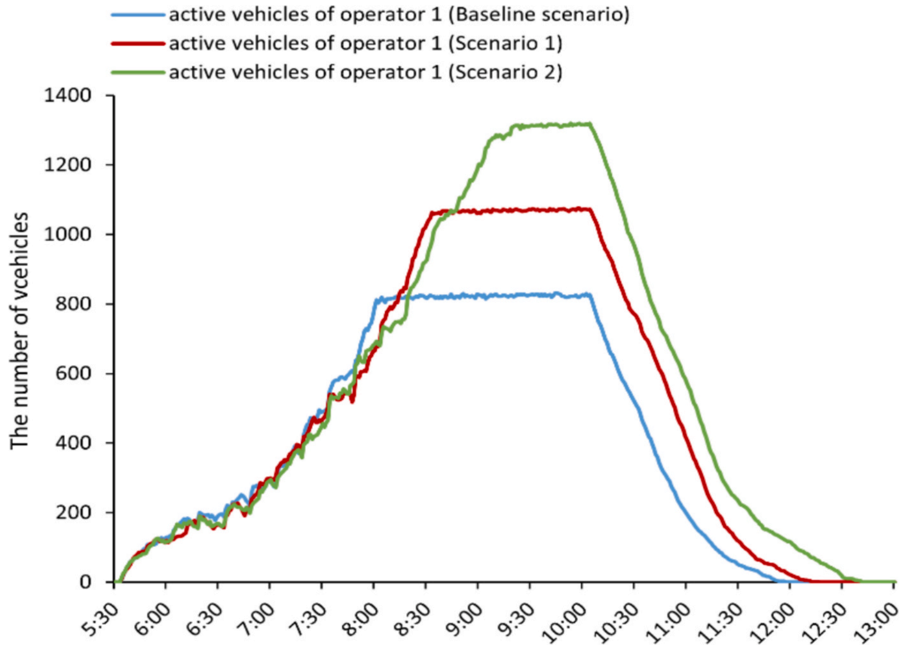

Fig. 9b. Active vehicles of operator 1 in simulation scenarios over time(hh:mm, 24-hour format).

maximise profit. A relatively low fare in this study is assumed (60% of the existing MoD that is active in the case-study city) to calculate the profits of operators based on the works by Oh et al. (2020) and Spieser et al. (2014), and an optimal pricing scheme is beyond the scope of this study.

6.2. Future directions

This paper presented a framework for modelling the AT systems with multiple independent operators (which are entering urban mobility markets). Through simulation, application scenarios with different fleet sizes and relocation operations are tested to help decision-makers (e.g., city authorities, fleet operators) identify multiple outcomes and impacts, leading to more effective strategic planning. Findings suggest that companies (operators) need to develop an effective relocation capability enabled by automated vehicle technologies to improve their competitive edge over their counterparts. However, operating AT services could deteriorate social welfare (e.g., more congestion with added ATs in the urban road network). Operators need to evaluate their operations or strategies carefully. The agent-based model provides a virtual environment to demonstrate the effectiveness of their strategy. The proposed framework is documented in a detailed and structured manner throughout the manuscript. Fig. 1 presents the overall model workflow and interaction between the core components, while Section 3 provides detailed descriptions of the simulation architecture and operational procedures related to AT relocation logic, assignment mechanisms, and

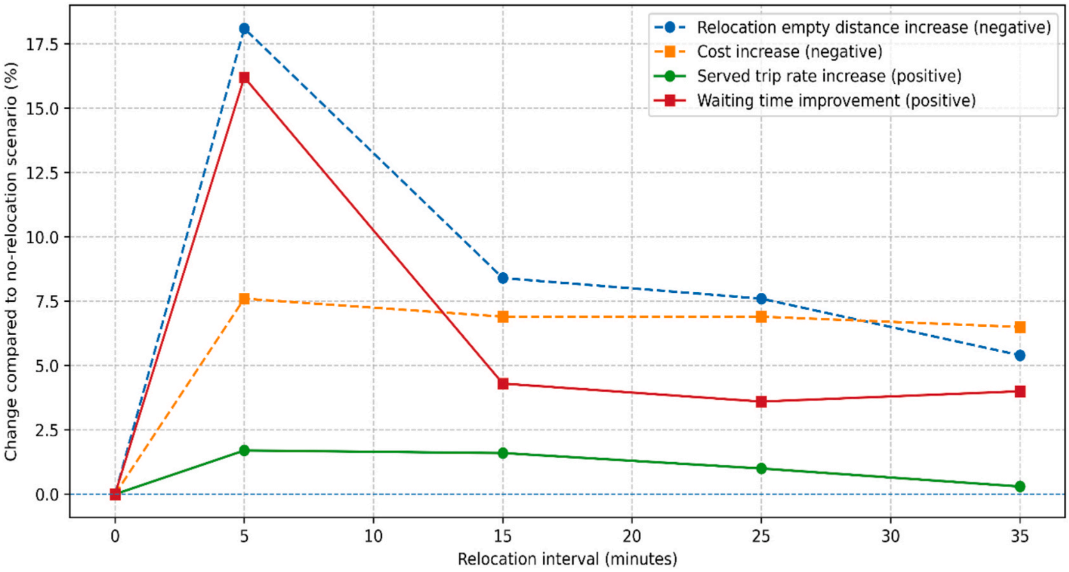

Fig. 10. Sensitivity Analysis of relocation Intervals and their performance Impacts.

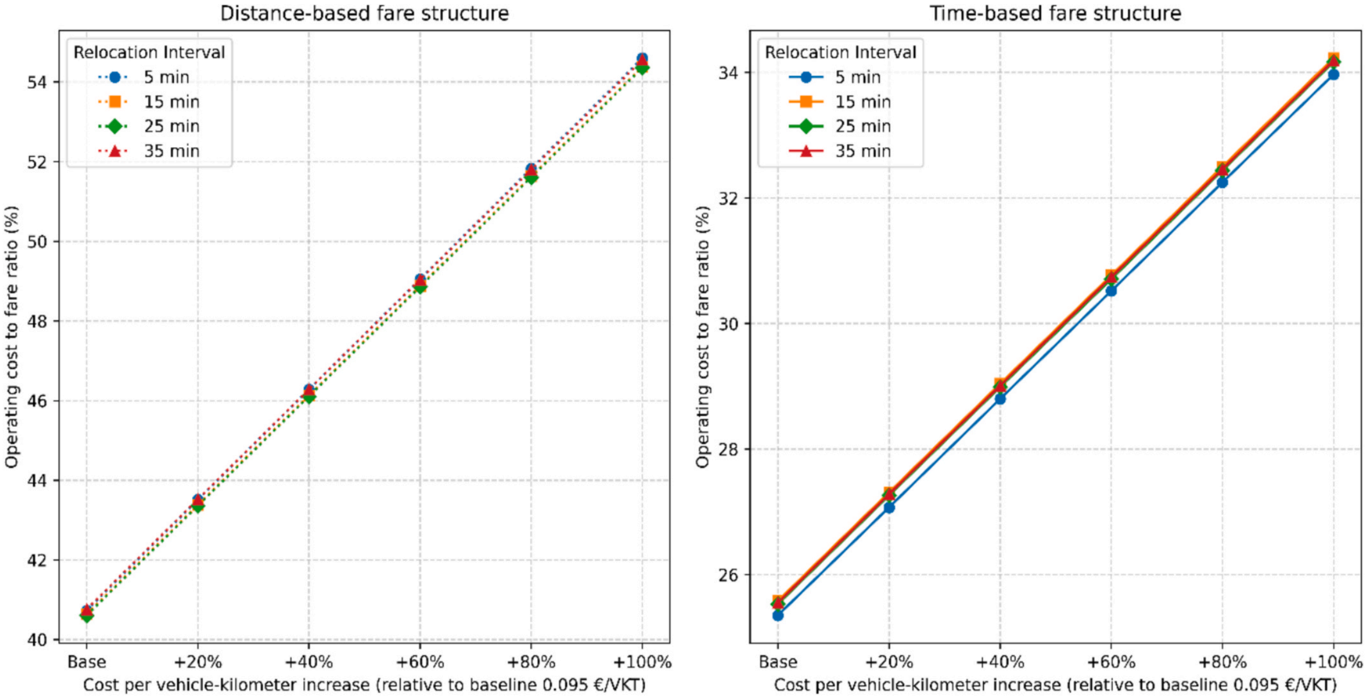

Fig. 11. Operating cost sensitivity analysis under different fare structures and relocation intervals.

routing processes. Such methodological details are provided to support replication of key procedures and future methodological extensions.

This study has several limitations. First, travel requests are generated using zone-based trip data for the morning period only, and we do not model linked trips across the full day. Second, passenger demand is treated as exogenous, without accounting for mode shifts or adaptive passenger responses to relocation strategies. Further work will incorporate the activity scheduling decisions into the agent-based simulation to improve the behavioural realism of the AT relocation assessment. Finally, we assume single-occupancy AT services for matching and routing, and estimate relocation costs using a fleet-cost model established for single-occupancy operations; future work will provide an estimate of operating costs and investigate relocation performance while incorporating ridesharing operations.

AT systems are considered an important form of urban mobility innovation. AT systems in the presence of public transportation systems are a promising pathway to transform the current transportation systems. At this stage, we address the need for modelling AT operations and demonstrate the effectiveness of relocation operations. The multiple-operator system may be a system of multiple independent operators. As expected, the dream version appears to be an integrated system that combines different transport modes, payment systems and user information across cities. In this case, the operators could coordinate AT relocations with public transport and across operators to avoid oversupply or undersupply.

On fleet size effects, relocation strategies, and coordination challenges could inform urban mobility policies, such as regulating fleet sizes, congestion management, or advancing cooperative frameworks among operators. These aspects require further exploration through integrated studies that combine operator's objectives with broader societal and network-level effects. Further work is anticipated to jointly evaluate operational strategies with regulatory measures.

While recent large-scale studies have demonstrated substantial cross-regional variation in road-user behaviour and sensitivity to contextual factors such as traffic conditions, surrounding vehicles, and road infrastructure (Alam et al., 2025), incorporating such behavioural diversity goes beyond the scope of this work. Nevertheless, integrating insights from global behavioural datasets into the joint AT vehicle and service design is a promising direction for future research. Such extensions could support systematic evaluation of the efficiency and effectiveness of relocation strategies under different behavioural and traffic contexts.

Data and code availability statement

The travel demand data, generated relocation demand, and zone information used in this study are publicly available via FigShare at https://doi.org/10.6084/m9.figshare.30898142.

The source code and scripts used for post-processing, interactive map generation, relocation flow visualisation, and sensitivity analysis are publicly available at https://doi.org/10.6084/m9.figshare.30898244."

CRediT authorship contribution statement

Senlei Wang: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Supervision, Resources. **Hai Xiang Lin:** Writing – review & editing, Supervision, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A

Relocation vehicles, associated zone and relocation timing information.

Demander zone(zone ID)	Vehicle shortage (vehicles)	Supplier zone(zone ID)	The number of relocated vehicles	Relocation time
89	41	93	18	06:18 am
		101	13	
	52	90	15	07:18 am
		93	21	
92	56	87	15	06:33 am
		89	21	
	20	85	18	07:33 am
100	28	90	13	06:03 am
	22	90	16	06:33 am
107	21	93	14	06:03 am
	97	86	16	06:48 am
		93	17	
		97	14	
		123	13	
	42	90	18	11:03 am
		93	16	
112	20	93	20	06:33 am
	20	90	16	11:33 am
122	74	85	18	07:03 am
		90	20	
		93	14	
	Total Vehicle shortage: 493 vehicles		Total number of vehicles in relocations: 346 vehicles	

Data availability

I have shared the link to the data and code

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