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Dual-Mode Vehicle Routing in Mixed Autonomous and Non-Autonomous Zone Networks*

Breno Beirigo, Frederik Schulte, and R. Negenborn

Abstract— **Autonomous vehicles (AVs) are expected to widely re-define mobility in the future, transforming many solutions into autonomous services. Nonetheless, this development requires an expected transition phase of several decades in which some regions will provide sufficient infrastructure for AV movements, while others will not support AVs yet. In this work, we propose an operational planning model for mobility services operating in regions with AV-ready and not AV-ready zones. To this end, we model detailed automated driving areas and consider a heterogeneous fleet comprised of three vehicle types: autonomous, conventional, and dual-mode. While autonomous and conventional vehicles can only operate in their designated areas, dual-mode vehicles service zone-crossing demands in which both human and autonomous driving are required. For such a hybrid network, we introduce a new mathematical planning model based on a site-dependent variant of the heterogeneous dial-a-ride problem (HDARP). With a numerical study for the city of Delft, The Netherlands, we provide insights into how operational costs, service levels, and fleet utilization develop under 405 scenarios of multiple infrastructural settings and technology costs.**

Index Terms— **Autonomous Vehicles, Ride Sharing, Mobility Services, Autonomous Zones, Dual-Mode Vehicles**

I. Introduction

The advent of autonomous vehicles (AVs) represents a disruptive change to urban transportation systems. Traveling with shared, self-driving vehicles will become as affordable as using public transport since all expenses of purchasing, maintaining and insuring vehicles are distributed across a large user-base [1]. Moreover, the widespread adoption of such vehicles represents a step forward on urban sustainability since reduced vehicle ownership directly impacts congestion and parking requirements. In fact, several simulation studies (e.g., [2], [3], [4]) have shown that current vehicle rides of major urban centers could be adequately serviced using comparatively smaller fleets of shared autonomous vehicles (SAVs). Most of these studies, however, assume a full-automation setting, a mobility scenario which is currently far from reality. Many companies have been still testing SAE level 3 vehicles in which special conditions apply (e.g., mapped routes, fair weather, possible human intervention) and early versions of level 4 vehicles are likely to be limited to more controlled environments (e.g., freeways, restricted zones) [5], [6].

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During a transition phase to full-automation, regulatory barriers will prevent AVs to operate in areas requiring advanced driving capabilities (e.g., shared spaces). Hence, the introduction of AVs is likely to happen gradually, following not only technological advances but also the spread of automation-friendly infrastructures. Chen et al. [7], for instance, suggest that government agencies can dedicate certain areas of road networks exclusively to AVs. Such autonomous vehicles zones (AVZs) could enhance the performance of transportation networks, by facilitating the formation of platoons, for example. In essence, until automation level 5 is achieved, fleet operators have to employ both conventional and autonomous vehicles to guarantee maximum service coverage on partially autonomous infrastructures.

This paper investigates how the gradual evolution of autonomous infrastructures influences fleet composition as well as vehicle routing in a mobility service. We simulate the spread of automated driving areas in urban networks and analyze the operational performance of a heterogeneous fleet comprised of autonomous vehicles (AVs), conventional vehicles (CVs) and dual-mode vehicles (DVs). While CVs and AVs are only allowed to operate in their respective areas, DVs can freely drive throughout the entire network. We carry out the analyses for the city of Delft, The Netherlands, by creating various autonomous driving areas in the city's mobility network. Figure 1 illustrates a possible setting with autonomous and conventional driving zones in the example of Delft.

We define the problem as a mixed integer linear programming (MILP) formulation in Section II and describe how we generated the hybrid networks and set up the test cases in Section III. Moreover, we discuss the results of our exact

Fig. 1. Example of autonomous vehicle zone (AVZ) deployment in Delft, the Netherlands. In AVZs, infrastructure is ready to support automated driving.

implementation and present some managerial insights based on our experiments (Section IV) concluding with a summary of key insights and outlook on future work (Section V).

II. Problem definition

In this study, we introduce a multi-depot site-dependent dial-a-ride problem (MDSDDARP), an extension of the heterogeneous dial-a-ride problem (HDARP) introduced by Parragh [8]. Similarly to HDARP, the MDSDDARP consists of designing a cost-effective routing plan for a fleet of heterogeneous vehicles to attend a series of pickup and delivery requests with different modes of transportation. However, while in most HDARP variants the source of vehicle heterogeneity is associated to transportation requirements of hospitals' patients (e.g., wheelchair space, stretcher, patient seat), in MDSDDARP the compatibility relationship between customers and vehicles depends on the ability a vehicle has to access customer locations. This concept was first explored by Nag et al. [9] in the site-dependent vehicle routing problem (SDVRP), in which certain customer sites (e.g., congested areas) could only be serviced by specific types of vehicles (e.g., small-capacity vehicles). However, rather than basing on vehicle's dimensions or user preferences to determine user-vehicle compatibility, we rely on vehicle's driving capabilities (automated, conventional, and dual-mode) to decide whether they are allowed to service users in automated or conventional driving areas. We summarize the MDSDDARP as follows. Given:

- a hybrid street network comprised of an autonomous vehicle zone (AVZ) and a conventional vehicle zone (CVZ);
- a heterogeneous fleet comprised of three vehicle types: autonomous, conventional, and dual-mode; and
- a set of time-constrained transportation requests arising from either a CVZ or an AVZ.

The MDSDDARP consists of constructing a set of vehicle routes in such a way that:

- DVs can pickup and deliver customers in the entire network, whereas AVs and CVs can only operate in automated and non-automated driving areas, respectively;
- vehicles depart from multiple locations and can stop at the delivery location of their last attended customer;
- the capacity of a vehicle is not exceeded along its route;
- the ride time delay of a route does not exceed a limit d_{ride};
- the pickup time delay of a request does not exceed a limit d_{pk};
- a subset of the requests is attended (i.e., service denial is allowed);
- the total profit is maximized.

Figure 2(a) illustrates the problem for a fleet of three vehicles (A, C, and D) of different types (autonomous, conventional and dual-mode), and three requests (1, 2, and 3) spread over a hybrid street network. While pickup and delivery points of requests 2 and 3 lie entirely inside a single zone, passenger 1 must be picked up inside an AVZ and delivered in a CVZ location. Next, Figure 2(b) shows how we simplify this setup by eliminating intermediate nodes of the real-world street network and creating a viable transportation network where vehicles and passengers are connected by their shortest paths according to their site compatibility. While vehicle D is allowed to visit every pickup and delivery node, A can only visit the nodes inside the AVZ and C can only visit the nodes inside the CVZ. Notice that although the pickup point of request 1 is inside the AVZ, vehicle A is not connected to it, since A cannot reach request 1 destination. Undirected lines represent two-way paths between nodes (possibly non-symmetric) and directed lines highlight some of the problem's operational constraints, such as, vehicles can only start their route by visiting pickup points and there are not paths from request destinations to origins.

A. MILP formulation

The multi-depot site-dependent DARP is modeled on a directed graph $G = (N, E)$. The node set N is partitioned into $\{P, D, O\}$ where $P = \{1, ..., n\}$ is both the set of pickup nodes and request indices, $D = \{n+1, ..., 2n\}$ is the set of destination nodes and O is the set of origins $o(k)$ of vehicles $k \in K$. The set O is created to better simulate a free-floating mobility service in which vehicles depart from distinct points within the service area (rather than departing from a central station) and park nearby the delivery point of the last attended request upon finishing the service.

We consider that each vehicle $k \in K$ with capacity Q_k is from a type $m(k) \in T$, and every transportation request i can be served by a subset of vehicle types $T_i \subseteq T$. Consequently, the arc set E is defined as $E = \{(i, j, m) : i \in O,\ j \in P$ or $i, j \in P \cup D, i \neq j$ and $i \neq n + j$ for $m \in T\}$, so that there might have up to $|T|$ paths from i to j, each one having a travel time $t^m_{i,j}$. In this study, the set of types T coincides with the driving modes allowed in our hybrid maps (i.e., $T = \{AV, CV, DV\}$).

To each node $i \in N$ is associated a load q_i, corresponding to the number of passengers, so that $q_i \geq 0\ \forall i \in P$, $q_i = -q_{i-n}\ \forall i \in D$ and $q_i = 0\ \forall i \in O$. Additionally, the service duration d_i is the sum of passenger delays δ for entering/leaving a vehicle visiting node $i \in N$, so that $d_i = |q_i \delta|\ \forall i \in N$.

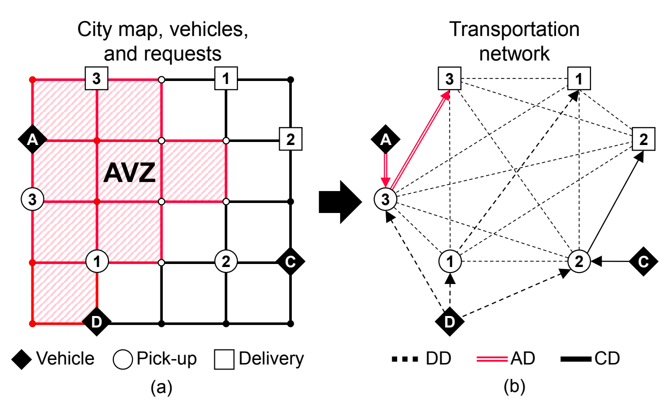

Fig. 2. (a) Real world input (hybrid street map, customer's pickup and delivery locations, and vehicle positions) and (b) corresponding viable transportation network.

TABLE I

MILP ENTITIES OF THE MDSDDARP

Sets	
K	Vehicles.
P	Pick-up nodes and request indices.
D	Delivery nodes.
O	Origin nodes $o(k)$ of vehicles $k \in K$.
N	$= P \cup D \cup O$.
V	Valid visits (k, i) for $k \in K$ and $i \in N$.
R	Valid rides (k, i, j) for $k \in K$ and $i, j \in N$.
T	Vehicle types.
Parameters	
$o(k)$	Origin point of vehicle $k \in K$.
Q^k	Capacity of vehicle $k \in K$.
α_k	Base fare for attending a passenger using vehicle k.
β_k	Distance rate for attending passenger using vehicle k.
$\gamma_{m(k)}$	Average operational cost/s (fuel, tolls, maintenance, labor, etc.) of vehicle k.
$m(k)$	Type of vehicle $k \in K$.
$t^{m(k)}_{i,j}$	Travel time from node i to node j in mode $m(k) \in T$ for vehicle $k \in K$.
δ	Time spent by a single passenger to enter/leave a vehicle.
d_i	Service duration at node $i \in N$ (i.e., sum of passenger's entering/leaving delays in i).
q_i	Number of passengers of request i.
d_{pk}	Maximum pickup time delay.
d_{ride}	Maximum ride time delay.
$[e_i, l_i]$	Pick-up time window of request i.
Variables	
$x^k_{i,j}$	Binary decision variable equal to 1 if vehicle $k \in K$ travels from point $i \in N$ to point $j \in N$.
τ^k_i	Arrival time of vehicle k at point i.
r^k_i	Time spent by request $i \in N$ in vehicle $k \in K$.
w^k_i	Load of vehicle $k \in K$ after visiting point $i \in N$.

Moreover, let d_{pk} be the maximum pickup delay, d_{ride} the maximum ride delay of all requests, and t_i the revealing time of request i. For a pickup and delivery pair (i, j) where $i \in P$ and $j \in D$, the earliest times (e_i and e_j) and latest times (l_i and l_j) to visit i and j are defined as follows: $(e_i, l_i) = (t_i, t_i + d_{\text{pk}})$ and $(e_j, l_j) = (e_i + d_i + t^m_{ij}, e_j + d_{\text{ride}})$ for driving modes $m \in T$.

The decision variable $x^k_{i,j}$ is equal to 1 if the arc $(i, j, m(k)) \in E$ is traversed by vehicle $k \in K$ and the load of a vehicle k upon leaving node $i \in N$ is w^k_i. Regarding the time related variables, r^k_i is the ride time of request $i \in P$ in vehicle k and τ^k_i is the time at which vehicle k arrives at node $i \in N$. Ultimately, in order to streamline model execution, a preprocessing phase is carried out to reduce the number of decision variables. We define R as the set of valid rides comprised of feasible (k, i, j) combinations and an auxiliary set of valid visits $V = \{(k, i) : (k, i, j) \in V \text{ or } (k, j, i) \in V\}$. Table I summarizes the sets, variables and parameters.

The formulation of the MDSDDARP is then as follows:

Maximize:

$$\sum_{\substack{(k,i,j)\in R\\ i\in P}} (\alpha_k + \beta_k t^{m(k)}_{i,n+i}) x^k_{i,j} - \sum_{(k,i,j)\in R} \gamma_{m(k)} t^{m(k)}_{i,j} x^k_{i,j} \tag{1}$$

Subject to:

$$\sum_{(k,i,j)\in R} x^k_{i,j} \le 1 \qquad i \in P \tag{2}$$

$$\sum_{(k,o(k),j)\in R} x^k_{o(k),j} \le 1 \qquad k \in K \tag{3}$$

$$\sum_{(k,i,j)\in R} x^k_{i,j} - \sum_{(k,i,j)\in R} x^k_{i,n+j} = 0 \qquad k \in K, j \in P \tag{4}$$

$$\sum_{(k,i,j)\in R} x^k_{i,j} - \sum_{(k,j,i)\in R} x^k_{j,i} = 0 \qquad k \in K, j \in P \tag{5}$$

$$\sum_{(k,i,j)\in R} x^k_{i,j} - \sum_{(k,j,i)\in R} x^k_{j,i} \ge 0 \qquad k \in K, j \in D \tag{6}$$

$$\tau^k_j - \tau^k_i \ge t^k_{i,j} + d_i + M^k_{i,j}(x^k_{i,j} - 1) \qquad (k, i, j) \in R \tag{7}$$

$$e_i \le \tau^k_i \le l_i \qquad (k, i) \in V \tag{8}$$

$$r^k_i = \tau^k_{n+i} - (\tau^k_i + d_i) \qquad i \in P, (k, i) \in V \tag{9}$$

$$t^{m(k)}_{i,n+i} \le r^k_i \le t^{m(k)}_{i,n+i} + d_{\text{ride}} \qquad i \in P, (k, i) \in V \tag{10}$$

$$w^k_j - w^k_i \ge q_j + W^k_{i,j}(x^k_{i,j} - 1) \qquad (k, i, j) \in R \tag{11}$$

$$max\{0, q_i\} \le w^k_i \le min\{Q_k, Q_k + q_i\} \qquad (k, i) \in V \tag{12}$$

$$x^k_{i,j} \in \{0, 1\} \qquad (k, i, j) \in R \tag{13}$$

$$w^k_i, \tau^k_i \in \mathbb{N} \qquad (k, i) \in V \tag{14}$$

$$r^k_i \in \mathbb{N} \qquad i \in P, (k, i) \in V \tag{15}$$

The objective function (1) maximizes the revenue obtained from passenger delivery while minimizing operational costs. Constraint (2) allows service denial, since not all customers need to be picked up, and constraint (3) defines that vehicles can potentially stay still in their origin nodes in case they are not scheduled. Constraint (4) imposes that if a vehicle visits a request pickup node it must also visit the associated delivery node. In turn, the flow constraints (5) and (6) ensure vehicles arrive and exit pickup nodes but may arrive and stay at delivery nodes, reflecting occasions in which a vehicle delivers its last customer and waits in the vicinity for incoming requests. Constraints (7) and (8) guarantee adequate arrival times at nodes within predetermined time windows while constraints (9) and (10) define and limit the ride time of each request. In turn, feasible load flows are guaranteed by constraints (11) and (12). Finally, the validity of W and M at the linearized constraints (7) and (11) is ensured by setting $W^k_{i,j} \ge \min\{2Q_k, 2Q_k + q_i\}$ and $M^k_{i,j} \ge \max\{0, l_i + t^k_{i,j} + d_i - e_j\}$ $\forall (i, j, k) \in R$.

III. SCENARIOS FOR AUTONOMOUS VEHICLE DEPLOYMENT

Assuming automated driving areas are gradually implemented, we establish three key elements that may influence the performance of future heterogeneous fleets: the cost depreciation of autonomous technologies (III-A), the configuration of mixed-zone street networks (III-B), and the particular demand patterns arising from such zoned environments (III-C).

TABLE II

OPERATIONAL COST SCENARIOS FOR VEHICLE TYPES IN RELATION TO AUTOMATION TECHNOLOGY (IN €/S)

Cost scenario	Vehicle type *AV*	*CV*	*DV*
S01 (large price premium)	0.004	0.002	0.005
S02 (moderate price premium)	0.003	0.002	0.004
S03 (minimal price premium)	0.002	0.002	0.003

A. Operational cost scenarios

It is widely assumed that AV technologies will become increasingly affordable until they eventually reach market saturation. Thus, we consider this gradual price depreciation to build three operational cost scenarios. In our study, operational costs vary according to the distance traveled (in seconds, considering an average speed of 40km/h) and are comprised of (I) general automotive costs (e.g., maintenance, parking, fuel, insurance), (II) driver's labor and (III) automation related costs (e.g., maintenance of extra sensors, software, data storage, computing power). In Table II, we show how these elements compose the total operational cost of each vehicle type for the potential scenarios $S01$, $S02$, and $S03$. Regardless of the vehicle type and scenario, we only vary the automation related costs (III), from 0.003€/s to 0.001€/s, while keeping general automotive costs (I) and driver's labor (II) stable at 0.001€/s each.

B. Mixed-zone street network

Since the development of dedicated automated areas is uncertain, we simulate the deployment of autonomous vehicles zones (AVZs). First, we use the python library OSMnx [10] to extract the map of Delft from OpenStreetMap and save it as a directed graph G comprised of edges (streets) and nodes (intersections). To guarantee any two nodes are connected to each other, we eliminate all nodes not belonging to the largest strongly connected component of G, resulting in a final graph with 2,123 nodes and 4,964 edges.

Generating AVZs consists of choosing z random nodes of this graph to be the zone origins and iteratively adding the neighboring edges and nodes from these origins, one level at a time, until at least an overarching coverage percentage p of strongly connected nodes within zones is achieved. In turn, all zones are interconnected by the shortest paths between their origins, yielding a strongly connected subnetwork representing a possible AVZ deployment. Figure 3 shows nine potential AVZ configurations for the street network in Delft considering a coverage percentage $p \in P = \{10\%, 25\%, 50\%\}$ and number of zone origins $z \in Z = \{1, 2, 4\}$. While z varies the spatial configuration of AVZs, p simulates their expansion, so that different transition scenarios can be assessed. To broaden the variability of our test cases even further, we repeat the generating process 5 times, resulting in 45 transportation networks with distinct configurations of automated driving areas.

Finally, assuming three modes of driving are available, automated driving (AD), conventional driving (CD) and dual-mode driving (DD), we create a look-up structure to store the shortest distances between every node and its reachable neighbors for each driving mode. Hence, a node belonging to an AVZ, for example, may access every node within the AVZ via automated driving paths whereas nodes outside the AVZ can only be accessed via dual-mode driving paths.

Fig. 3. Potential deployment of automated driving areas in Delft street network considering different combinations of number of zones z and coverage percentage p.

TABLE III

ZONE-CROSSING FREQUENCIES

Transportation pattern	Zone-crossing *High*	*Moderate*	*Low*
intra-zone ($AVZ - AVZ$)	10%	30%	40%
intra-zone ($CVZ - CVZ$)	10%	30%	40%
inter-zone ($AVZ - CVZ$)	80%	40%	20%

C. Transportation demand vs. zone configuration scenarios

OD data is randomly generated to assess distinct demand distributions based on the transportation patterns of the passengers in relation to the configuration of AD areas. This way we can investigate what is the logistical outcome when transportation demands are restricted to a particular area (intra-zone transportation) or when origin and destination nodes belong to different zones (inter-zone transportation). To do so, we consider three zone-crossing frequencies (low, moderate, and high) as shown in Table III. Additionally, we investigate the implication of busy operational environments by uniformly distributing such demands on different time intervals, namely, 1, 2, 5, and 10 minutes.

IV. NUMERICAL STUDY

Using the scenarios defined in Section III, we describe how we set up our test cases (Section IV-A) and discuss the significance of our findings (Section IV-B). Results are expressed in terms of the following performance marks:

- *Service level:* the percentage of attended requests.
- *Fleet utilization:* the percentage of the fleet actually used to service requests.

- *Mobility cost:* the relative operational cost to service each request.
- *Execution time:* the sum of preprocessing time (for creating a suitable transportation network and setting up the MILP model) and the solver runtime.
- *Fleet composition:* Percentages of each vehicle type that compose the final make-up of used vehicles.

A. Test case configuration

Table IV summarizes the parameters we consider to generate a total of 14,580 test cases, and Table V defines values for service and fleet configuration parameters presented in Section II-A. Instances are run for up to 10 min (not including preprocessing times) using an Intel Xeon 3.7Ghz computer with 32GB RAM and the MILP model is implemented using the Python interface of the Gurobi 7.5.2 optimizer.

B. Results

Under the time boundary specified, optimal results were obtained in 91% of the test cases. We then use this optimal subset of results to carry out our analysis, assessing mean values of test cases grouped by different parameters (e.g., a result defined by number of vehicles, number of requests, and operational cost scenarios, can be the mean of up to 540 tests cases). In the following sections, we enumerate our main findings.

1) Time interval and fleet performance: The busier the logistical scenario, the higher the fleet utilization, and the fewer requests can be serviced. This trend can be verified in the average percentages of service level and fleet utilization presented in Table VI, and it is especially remarkable when a large number of requests must be serviced by few vehicles.

2) Fleet composition & AD coverage: Fleet composition depends on the AD coverage once AVs and DVs are more prone to be scheduled when larger areas of the transportation network can accommodate autonomous driving. Figure 4 illustrates this trend. Each square represents the average percentage of a vehicle type for each combination of AD coverage, zone-crossing frequency, and operational cost scenario. Notice that within each zone-crossing category, the share of AV and DV vehicles tends to grow while the opposite occurs to CVs. Larger AVZs may lead to farther AV trips, making vehicles busier for longer periods and preventing them serving other customers. Hence, to comply with the service time constraints, the size of AV fleets must follow the growth of AVZs, whereas the size of CV fleets must follow the shrinkage of CVZs.

3) Fleet composition and zone-crossing frequencies: Although 80% of the requests must be serviced by DVs when a high crossing frequency is considered, this share is not directly reflected in the shares of DVs actually scheduled, which were around 50% no matter the AD coverage and cost scenario. This subpar representation may be associated with the dimension of our transportation network: travel times between pickup and delivery nodes are generally short, so that fewer vehicles can service several customers. In contrast, actual DV shares for the low and moderate inter-zone frequencies more closely resemble their correspondent zone-crossing frequencies in Table III.

TABLE IV

SUMMARY OF TEST CASE SETTINGS TOTALING 14,580 INSTANCES

Parameter	**Values**
Number of vehicles	$\{15, 30, 60\}$
Number of requests	$\{10, 20, 40\}$
Operational cost scenarios	{S01, S02, S03}
AD coverage percentage	$\{10\%, 25\%, 50\%\}$
Number of AD zones	$\{1, 2, 4\}$
Zone-crossing	{high, moderate, low}
Time interval (min)	$\{1, 5, 10, 20\}$
Number of zone configurations	5

TABLE V

SERVICE AND FLEET CONFIGURATION PARAMETERS

Parameter	**Value**
Base fare α_k	€3.0
Distance rate β_k	€0.001
Vehicle capacity Q_k	5
Entering/leaving vehicle delay δ	30 s
Pickup delay d_{pk}	5 min
Ride delay d_{ride}	10 min

TABLE VI

SERVICE LEVEL AND FLEET UTILIZATION ON DIFFERENT TIME INTERVALS, NUMBER OF VEHICLES AND REQUESTS

		Service level				**Fleet utilization**			
#R	**#V**	***01min***	***05min***	***10min***	***20min***	***01min***	***05min***	***10min***	***20min***
10	**15**	93.9%	96.5%	97.9%	99.4%	60.2%	58.6%	56.1%	51.8%
	30	99.4%	99.7%	99.7%	100.0%	31.9%	31.1%	30.3%	29.1%
	60	99.8%	100.0%	99.8%	100.0%	16.1%	16.0%	15.9%	15.6%
	Avg.	97.7%	98.7%	99.1%	99.8%	36.1%	35.2%	34.1%	32.1%
20	**15**	71.3%	80.4%	89.4%	96.5%	86.4%	87.2%	84.8%	80.7%
	30	97.1%	98.2%	99.6%	99.8%	60.2%	57.3%	54.5%	50.9%
	60	99.8%	99.9%	100.0%	100.0%	31.5%	30.6%	29.9%	28.9%
	Avg.	89.4%	92.9%	96.3%	98.8%	59.4%	58.4%	56.4%	53.5%
40	**15**	41.8%	49.8%	63.4%	84.5%	94.6%	93.6%	95.9%	95.8%
	30	75.5%	87.1%	94.2%	98.6%	87.8%	88.1%	82.1%	76.9%
	60	97.7%	99.3%	99.7%	99.8%	59.2%	56.1%	52.6%	49.1%
	Avg.	71.6%	78.7%	85.8%	94.3%	80.5%	79.2%	76.8%	73.9%

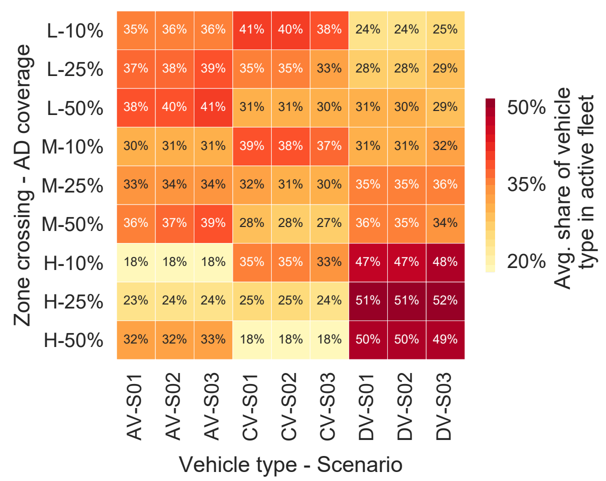

Fig. 4. Fleet composition according to automated driving coverage (10%, 25% and 50%), zone-crossing frequency (L=Low, M=Moderate, and H=High) and operational cost scenarios (S01, S02, and S03).

TABLE VII

OVERALL TEST CASE RESULTS FOR EACH OPERATIONAL COST SCENARIO AND NUMBER OF VEHICLES AND REQUESTS

#V	#R	Service level	Fleet utilization	Mobility cost (€) *S01*	*S02*	*S03*	Pre. (s)	Run. (s)
15	**10**	96.9%	56.7%	1.43	1.19	0.92	0.0	0.1
	20	84.4%	84.8%	1.43	1.17	0.91	1.5	2.7
	40	59.8%	94.4%	1.29	1.07	0.83	9.2	459.3
30	**10**	99.7%	30.6%	1.27	1.05	0.82	0.5	0.3
	20	98.7%	55.7%	1.30	1.08	0.84	3.4	1.5
	40	88.2%	83.3%	1.31	1.08	0.84	18.9	188.9
60	**10**	99.9%	15.9%	1.17	0.96	0.75	2.0	0.7
	20	99.9%	30.2%	1.17	0.97	0.75	7.2	3.2
	40	99.0%	54.2%	1.21	1.00	0.78	38.8	72.9

4) Fleet composition & operational cost scenarios: The depreciation of automated driving was found to be virtually irrelevant, especially at high zone-crossing frequencies. In such cases, there is no leeway for replacing conventional vehicles once most of the trips expressly require dual-mode vehicles, so that it is more likely that such vehicles end up being used to also service intra-zone requests, no matter the operational costs in place. In contrast, if a low zone-crossing frequency is considered, the share of AVs and DVs slightly increases whereas the share of CVs decreases: former DV rides are replaced by AV rides and former CV rides are replaced by DVs.

5) The influence of operational costs: As expected, the depreciation of autonomous vehicle operational costs decreases mobility costs (see Table VII). Independently of the operational cost scenario, mobility costs tend to decrease as more vehicles are available since trip distances can be shorter. Additionally, the results also help define the tradeoff between fleet size, and operational costs for a number of requests.

6) Execution time: As shown in Table VII, the preprocessing time (Pre.) is directly related to the number of vehicles and requests since it consists of looping through all decision variables to eliminate unfeasible answers. In contrast, the runtime (Run.) seemed to be more sensitive to the scarcity condition posed by certain operational environments than by the number of decision variables and constraints. In fact, the busier the operational environment, the longer the runtime: small fleets dealing with a far superior number of requests (e.g., 15 vehicles and 40 requests) are a more complex challenge to the branch-and-bound method of Gurobi solver.

V. CONCLUSIONS & FUTURE RESEARCH

In this study, we investigated how mixed-zone transportation networks can affect mobility services in the light of the gradual development of autonomous infrastructures. We model the routing for such services considering a heterogeneous fleet comprised of conventional, autonomous, and dual-mode vehicles, and assume that only the latter can freely access every location in the network. In contrast, autonomous and conventional vehicles are restricted to operate in automated driving areas and non-automated driving areas, respectively. Then, such vehicle/infrastructure compatibility requirement is used to formulate the problem as a variant of the heterogeneous dial-a-ride problem in which site-dependencies are taken in consideration.

The results obtained with numerical experiments for the city of Delft, The Netherlands provide detailed insights into how operational costs, service levels, and fleet utilization develop under scenarios of multiple infrastructural characteristics, fleet configurations, and technology costs in the next decades of vehicular automation. In this way, the work builds a foundation for the increasingly important problem domain of partially autonomous vehicle routing and the design of future mobility services for such conditions.

The presented results let urban planners understand the importance of infrastructural decisions for the quality of local mobility services, and transportation providers gain fundamental insights on how to adjust a fleet to infrastructural conditions of cities. In this respect, the results show that an ideal fleet composition is not driven by changes in operational costs but is strongly associated with coverage of autonomous vehicle zones and demand patterns. The functions of traffic planning and fleet management may therefore converge increasingly in future, and advanced data analysis will be essential for the quality of such (partially) autonomous mobility services. Future work will therefore incorporate analytics based on large-scale, real-world demand data from major urban centers and also consider the real-time dynamics of vehicle routing.

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