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An Assignment-Based Dispatching Heuristic For Agglomeration-Scale AMoD: Sensitivity Analysis Of The Demand Prediction Horizon On The Benefits For Supplier And Customers --Manuscript Draft--

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1 **AN ASSIGNMENT-BASED DISPATCHING HEURISTIC FOR**
2 **AGGLOMERATION-SCALE AMOD: SENSITIVITY ANALYSIS OF THE DEMAND**
3 **PREDICTION HORIZON ON THE BENEFITS FOR SUPPLIER AND CUSTOMERS**

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1 ABSTRACT

2 As shared mobility solutions are developing, the next generation of e-ride-hailing systems are an-
3 nounced to be based on self-driving vehicles. Autonomous Mobility on Demand (AMoD) could
4 enhance the level of service experienced by travelers thanks to lower repositioning costs and cen-
5 tralized control of compliant vehicles. The dispatching strategy determines system performance
6 from AMoD and travelers' points of view. Rule-based heuristics do not exploit the full potential
7 of the fleet because they are myopic to future requests. The rolling horizon approach allows to
8 anticipate and make better dispatch decisions. In this study, we question the benefits for AMoD
9 and travelers to include a short/mid-term demand prediction in an assignment-based heuristic. We
10 define four variants of the assignment-based approach, with order matching only or joint order
11 matching + fleet management, with impatient or productivist AVs. In a theoretical agglomeration,
12 we test the sensitivity of horizon length on AMoD's profit, order response rate and, travelers' wait-
13 ing times under the four strategies. We carefully study the outcomes of the profit-oriented heuristic
14 in terms of equity.

15

16 *Keywords:* rolling horizon, dispatching, heuristic, autonomous mobility on demand, morning com-
17 mute, equity

1 INTRODUCTION

2 Recently, shared mobility solutions are booming and take several forms: carsharing, bikesharing,
 3 scooter sharing, ridesharing, ridesourcing, and e-ride-hailing (1). The latter service type uses
 4 smartphone apps to connect drivers with passengers (e.g., Uber). It involves three stakeholders:
 5 the transportation network company (TNC), drivers, and travelers.

6 The next generation of e-ride-hailing systems may remove drivers from the equation. Au-
 7 tonomous Mobility-on-Demand (AMoD, (2)) systems, based on autonomous vehicles (AVs), at-
 8 tract investments from car manufacturers, mobility companies and, digital corporations (3). Com-
 9 pared to traditional e-ride-hailing, AMoD operational cost is awaited to be reduced thanks to sav-
 10 ings on wages (4). Repositioning is facilitated, and surge-pricing, traditionally operated by TNC
 11 to balance supply and demand, is no more relevant with compliant vehicles. Static fares and a
 12 sufficient level of service encourage adoption by users for recurrent trips. It is an opportunity to in-
 13 crease the vehicle utilization rate and reduce car ownership in urban areas. The centralized control
 14 of vehicles allows to adopt fleet-wide strategies and make more optimal dispatch decisions.

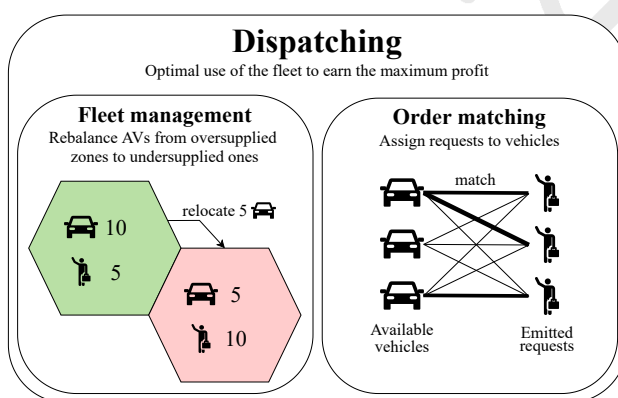


FIGURE 1: AMoD dispatching.

15 Dispatching encompasses fleet management for rebalancing AVs from oversupplied to un-
 16 dersupplied areas and order matching for assigning customers to AVs, as shown in figure 1. The
 17 dispatcher module is the cornerstone of a system composed of AMoD and demand. It is under
 18 the management of the private AMoD operator. In practice, operators' first interest may not be to
 19 deliver the highest quality of service equally over its coverage area but to maximize its profit. Trav-
 20 elers' objective is to minimize their travel costs. The dispatcher determines AMoD and travelers'
 21 outcomes by receiving AVs' positions, service plannings, capacities, travelers' requests, timing
 22 constraints, and connecting their respective objectives. Understanding the impact of the dispatch-
 23 ing strategy chosen on these metrics is worthwhile.

24 Real-time dispatching is the only option when the environment is highly dynamic and
 25 AMoD has no knowledge about future requests. Rule-based heuristics are used in this case. The
 26 most largely used heuristics are presented in (5). The *nearest-idle-vehicle* assigns the nearest cur-
 27 rently idle vehicle to the request that has just been emitted in the oversupply regime and assigns the
 28 oldest request to the vehicle that has just turned available in the undersupply regime. The *nearest-*
 29 *vehicle* matches the nearest vehicle for which future availability time is known, to the oldest open
 30 request. The *nearest-idle-vehicle/nearest-open-request* matches the nearest open request with the
 31 vehicle that has just turned available in the undersupply regime approaches (6). The first heuristic

1 is nearly random in the undersupply regime, the second sticks to FIFO rule for requests, the third
 2 relaxes FIFO rule but remains myopic. They all proceed to local optimization by considering a
 3 single request or vehicle. They try to maximize the number of customers served by chasing each
 4 new request without considering the profitability associated with a match.

5 To improve dispatching decisions, we need an estimation of future requests via enabling
 6 reservation, predicting coming requests with historical data, or both. (7) has highlighted the gap
 7 between exact offline optimization methods, with full knowledge of demand on the studied period,
 8 and rule-based heuristics. In practice for AMoD, the horizon of prediction cannot be so long. Given
 9 the uncertainties inherent to on-demand systems, a short/mid-term horizon is more reasonable. The
 10 rolling horizon, introduced by (8), is the state-of-the-art approach to deal with sequentially growing
 11 knowledge about future requests. Exact optimization methods have employed it.

12 The most popular formulation enabling exact optimization of dispatch decisions is the Dial-
 13 a-Ride Problem (DARP) (9). This formulation builds a set of routes to maximize a certain objective
 14 function. They are at least two decision variables: binary variables indicating if a vehicle travels
 15 between two pick-up/drop-off nodes and the times at which each vehicle starts to serve a node
 16 (10). The sophisticated algorithms required to solve DARPs lack scalability. They hardly adapt to
 17 large-scale and real-time applications in highly dynamic scenarios. Indeed, the more uncertain the
 18 prediction on the horizon is, the more often routes should be re-optimized. Notably, (11) review
 19 refers to (12) (300 customers) and (13) (900 customers).

20 We propose a new assignment-based heuristic using the rolling horizon principle in this
 21 study. It is far less myopic than the rule-based heuristics presented above while remaining much
 22 simpler and scalable compared to routes optimization addressed by the DARP. Figure 2 summa-
 23 rizes our positioning. Inspired by (14), our approach stands out due to the anticipation of future
 24 requests. In the latter reference, the dispatcher remains reactive. It reacts to the receipt of newly
 25 emitted requests. The availability of vehicles is the only element shortly anticipated. Our approach
 26 cyclically recalculates the best assignment of current and future open requests with vehicles that
 27 are or will be soon available. At each call, it solves a maximization problem where the objective
 28 function reflects its total expected profit on the coming horizon.

	Long-sighted	Short/Mid-term horizon	Myopic
Demand forecast			
AMoD policy	Mandatory reservation ahead of the simulated period	Possible reservation Demand forecast module	No reservation possible No demand forecast module
Dispatching strategy	Routes builder (DARP for small instances)	Route builder (DARP for small instances) Assignment-based heuristics	Rule-based heuristics

FIGURE 2: Positioning.

29 Primarily, we question the gains emerging from the knowledge of future requests in a the-
 30 oretical scenario where consequent repositioning efforts are required from AVs. Gains are in-
 31 vestigated from the AMoD side (profit) and travelers side (availability of service, pick-up time),

1 considering that the dispatching process favors only the former. On travelers' side, the experi-
2 enced level of service is weighted against traveler's dependency on AMoD, which is approached
3 thanks to the modeling of the whole multimodal network in our simulation platform. Two profit
4 estimation strategies are investigated: one where early arrival of AV at a pick-up point is penalized,
5 and another where the profit earned per elapsed time is preferred. We also explore two types of
6 matching: one with permanent matches on the whole horizon (order matching only), another with
7 permanent matches on the first part of the horizon, and temporary matches for repositioning vehi-
8 cles on pick-up points awaited for the second part of the horizon (joint order matching and fleet
9 management). A sensitivity analysis of the horizon length on these gains under the different dis-
10 patching strategies allows to define the best configuration for each stakeholder. Finally, a pricing
11 scheme to conciliate AMoD and travelers' interests is inspected.

12 Briefly, our contributions are: (i) the implementation of a simple and scalable assignment-
13 based heuristic configured with four strategies to render AMoD's profit-oriented dispatcher; (ii)
14 the development of a platform to simulate customers and AMoD interactions, where alternative
15 itineraries are modeled to assess for travelers willingness to wait for being picked-up; (iii) in a
16 Manhattan-like network, the sensitivity analysis of horizon length, fleet size and planning length
17 on travelers-side service efficiency and AMoD-side profits.

1 AN ASSIGNMENT-BASED HEURISTIC ANTICIPATING FUTURE REQUESTS

2 Hypotheses on AMoD

3 First, AMoD manages every single AV composing the fleet. The dispatching decisions are made
4 in a centralized manner. Considering a centralized dispatcher allows better decisions than a de-
5 centralized system where each AV would be responsible for its routing, relocating, and pick-up
6 actions.

7 As announced, we assume AMoD has access to an estimation of future requests. Demand
8 forecast can be achieved by allowing reservation and analyzing historical data (15–17). The fore-
9 caster module is out of the scope of this study. We suppose that it provides a perfect knowledge
10 of demand within the coming horizon. As our main focus is the benefits that can emerge from the
11 introduction of a horizon, this hypothesis allows us to draw the upper bound of what each proposed
12 heuristic strategy can achieve.

13 Another assumption is that AMoD has no long-term economic strategy. It has a unique
14 fixed fare scheme over the greater urban area. This fare scheme is made to be competitive while
15 ensuring lucrative rides for AVs. It is expected to be more attractive economically for travelers than
16 today’s (e-)ride-hailing services. One of the most popular fare scheme in literature (18–21) is used
17 here. Values for base, distance-based, and time-based fares are chosen to overcome the production
18 cost (22) of any ride an AV performs. Money is effectively earned for a ride.

19 Algorithm

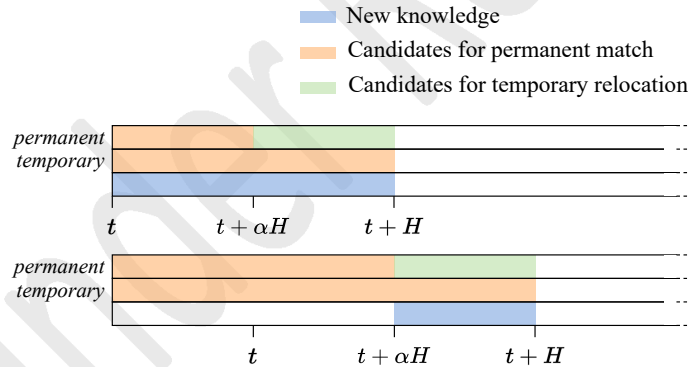


FIGURE 3: Rolling horizon principle for *permanent* and *temporary* modes.

20 Let t be the current time. At t , AMoD is aware of all requests already emitted and requests that
21 will be emitted between t and $t+H$. The set of known open requests is noted R_H . A request is said
22 open when it has not been permanently matched and has not been canceled by traveler yet. Each
23 open request $j \in R_H$ is characterized by an earliest pick-up time e_j (which is equal to the request
24 time in our case) and a latest pick-up time l_j . A maximum waiting time w_j is defined for each
25 traveler ($l_j = e_j + w_j$). As we focus on ride-hailing, the capacity of all AVs is set to one. We call A
26 the set of available AVs. An AV is said to be available when it has no more than $K \geq 0$ requests in
27 its service list. The service list corresponds to an activity planning for the AV. It comprises service
28 missions only. The rolling horizon principle is represented on figure 3.

29 We implement two modes in the algorithm: a permanent matching mode (*permanent*) and,
30 a short-term permanent matching / long-term temporary repositioning mode (*temporary*). In *per-*

1 *manent* mode, all matches identified by the optimal assignment resolution method are made per-
 2 manent. In *temporary* mode, only matches implying a request j satisfying $e_j \leq t + \alpha H$ ($\alpha \in [0, 1]$)
 3 are made permanent. Other matches (i, j) identified are so that $e_j > t + \alpha H$. They lead to the ini-
 4 tiation of repositioning movements by concerned AVs. A repositioning movement is not a service
 5 mission. The match is not registered in AV's service list. At the next optimal assignment resolu-
 6 tion method call, relocating AVs are thus considered available. Note that repositioning movements
 7 are only accessible to idle AVs (having no mission in their service list). The *temporary* mode in-
 8 creases AMoD flexibility by putting back into play a part of the decisions taken. In this mode, the
 9 dispatcher does achieve order matching jointly with fleet management. In both modes, the horizon
 10 is rolling, i.e., the optimal assignment algorithm is called each αH . Since demand prediction is
 11 perfect, it is unnecessary to call it more often. The dispatch algorithm is detailed below.

Algorithm 1: Dispatch algorithm

- 1 Initialize A with all AVs, R_H to an empty list, $t = 0$
 - 2 Set horizon to $[t, t + H]$, gather requests j emitted within the horizon and append them
to R_H , gather AVs i with at most K requests in their service list to form A
 - 3 Calculate utilities u_{ij} for each (i, j) pair
 - 12 4 Form a bipartite graph with u_{ij} as cost on arcs and compute the matching maximizing
the sum of utilities
 - 5 *permanent*: Make permanent all assignments decided in step 4. *temporary*: Make
permanent all assignments decided in step 4 for which $e_j \in [t, t + \alpha H]$, and initiate
temporary repositioning movements for the other matches decided. Both: Remove
permanently matched j from R_H
 - 6 Set $t = t + \alpha H$ and go to step 2.
-

13 Impatient and productivist utilities

14 A request $j \in R_H$ is characterized by a brut revenue p_j , which is the price traveler pays to the AV.
 15 The AMoD fare scheme is defined as:

$$16 \quad p_j = f_0^a + f_d^a d_j + f_t^a t_j \quad (1)$$

17 where f_0^a is the base fare, f_d^a is the distance-based fare f_t^a is the time-based fare, d_j is the travel
 18 distance of the path traveler wants to ride onboard AV, t_j the travel time on this path.

19 The pair (i, j) designates a potential match between i and j . It is characterized by d_{ij} , the
 20 distance on the shortest path between i and j 's pick-up point, t_{ij} , the travel time on this path, and u_{ij}
 21 the utility of match computed in step 3 of the algorithm. We define two strategies AMoD can adopt
 22 to maximize its profit. The *impatient* strategy (equation 2) takes into account the repositioning cost
 23 of i toward j 's pick-up point, the expected revenue for serving j , the eventual time lost by i while
 24 waiting for traveler departure e_j . The waiting time AV experience by arriving early at a pick-up
 25 point is penalized. The *productivist* strategy (equation 3) takes into account the repositioning cost
 26 and the expected revenue into a profit per time unit. Earning more profit in less time is favored.

$$u_{ij}^{impatient} = -C_d^a d_{ij} + (p_j - C_d^a d_j) \xi_{ij} - f_t^a \max(0, e_j - (t_i + t_{ij})) \quad (2)$$

$$u_{ij}^{productivist} = \frac{-C_d^a d_{ij} + (p_j - C_d^a d_j) \xi_{ij}}{t_{ij} + \max(0, e_j - (t_i + t_{ij})) + t_j} \quad (3)$$

1
2 where C_d^a designates the distance-based operation cost of an AV, t_i is the time at which i will drop-
3 off the last traveler currently appearing in its service list ($t_i = t$ if there is no mission in i 's service
4 list), ξ_{ij} equals 1 if $t_i + t_{ij} \leq l_j$, 0 otherwise (no profit can be earned if AV arrives too late). Note
5 that AMoD is assumed to know l_j and e_j .

6 Optimal assignment

7 In step 4 of the algorithm, the following optimization problem is solved:

$$\max_{x_{ij}} \sum_{i \in A} \sum_{j \in R_H} u_{ij} x_{ij} \quad (4a)$$

$$\text{subject to } x_{ij} \in \{0, 1\}, \forall i \in A, \forall j \in R_H \quad (4b)$$

$$\sum_{i \in A} x_{ij} \leq 1, \forall j \in R_H \quad (4c)$$

$$\sum_{j \in R_H} x_{ij} \leq 1, \forall i \in A \quad (4d)$$

8
9 where x_{ij} are the binary decision variables, equal to 1 if (i, j) match is decided, 0 otherwise.
10 To prevent unfavorable interactions between two assignments for one AV decided during the same
11 dispatch round, constraint 4c imposes that an AV can be assigned to at most one request per optimal
12 assignment resolution call. Indeed, when several matches are allowed for one AV i , utility u_{ij} , $j \in$
13 R_H , is directly dependent on the assignment of other requests to the same AV. Separately, matches
14 $(i, 1)$ and $(i, 2)$ can have high utilities, but it does not mean that utility of a route including customers
15 1 and 2 has a good utility. Here is the main difference between routes building and assignment
16 approaches. The former computes routes utilities, the latter computes assignment utilities. Due to
17 constraint 4c, there is a risk for under-exploited AVs. Some AVs may finish their mission before
18 the next call of the optimal assignment problem and remain idle for a few minutes. To prevent
19 this phenomenon, we properly set α to and enable AVs to have more than one service mission in
20 their planning (at most K , where missions are appended in different calls of the optimal assignment
21 resolution). The value of α should not be too small to keep the scalability of the method and not
22 too big to limit the number of lost resources between two calls. It should be consistent with the
23 average riding time of a service mission. Finally, constraint 4d ensures that a request is matched
24 with at most one AV.

25 A benchmark heuristic

26 To evaluate the benefits of including a demand prediction, we want to compare our assignment-
27 based anticipative dispatch with a rule-based myopic heuristic. We implement a *nearest-vehicle/nearest-*
28 *open-request* dispatcher. Contrary to our algorithm, which regularly calls the optimal assignment
29 resolution, this is an event-based approach. Dispatcher is triggered whenever a new request is
30 received in the oversupply regime and whenever an AV turns available (it has just dropped off a
31 traveler so that its service list has strictly less than K requests) in the undersupply regime. The
32 dispatcher is completely myopic to future requests. It does not completely stick to FIFO rule con-
33 trary to *nearest-idle-vehicle* and *nearest-vehicle* strategies and, shortly anticipates AVs availability

1 contrary to *nearest-idle-vehicle/nearest-open-request* heuristic. The selection is done according to
 2 the following equations:

$$i^* = \underset{i \in A}{\operatorname{argmin}}(t_i + t_{ij}) \quad (5)$$

where j has just been received.

$$j^* = \underset{j \in R_H}{\operatorname{argmin}}(t_i + t_{ij}) \quad (6)$$

3 where i has just turned available.

4 **SIMULATING AMOD-TRAVELERS INTERACTIONS**

5 AMoD and travelers interact within an environment representing a theoretical agglomeration. We
 6 developed a simple simulation platform that focuses on the elementary bricks required to study the
 7 impact of the horizon on supplier and customers' benefits.

8 **Realistic distances and travel times**

9 Since distances and travel times determine indicators we want to assess, consistent parameters
 10 should be provided to the optimal assignment problem. The simulator takes a road network as an
 11 input. In our theoretical agglomeration, we chose a Manhattan road network with three mesh sizes
 12 to account for topology differences over the greater urban area. The smaller mesh size stands in the
 13 center of the city (U_1), the medium one in the suburbs (U_2), the biggest one in the extended suburbs
 14 and the close rural area surrounding the city (U_3 , figures 4a and 4). Two ring roads are added on
 15 the boundaries between U_1 - U_2 (U_{12}) and U_2 - U_3 (U_{23}). A fixed mean speed (v_{U_k}) for cars and AVs
 16 is defined in each urban zone. Vehicles travel arcs of the network node by node at mean speed.
 17 Traffic dynamics are not modeled here. In addition, since the number of AVs circulating remains
 18 limited compared to background traffic, we assume they have no impact on the known mean speed.
 19 Adding a macroscopic traffic model such as MFD (23) to account for traffic dynamics and AVs'
 20 contribution to congestion will be studied in future research.

21 **A consistent demand addressed to AMoD**

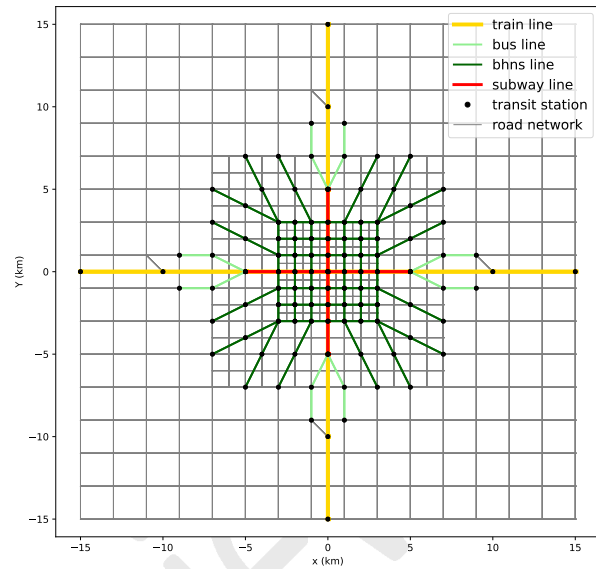
22 Applying an itinerary choice on a global demand pattern allows to better render the distribution
 23 of pick-up and drop-off points over the agglomeration compared to a random generation. We thus
 24 model the entire multimodal network.

25 *Multimodal network*

26 To represent the different transportation modes including walk (w), car (c), AV (a), train (r), sub-
 27 way (s) and bus (b), a digraph $G = (V, A)$, as the one shown in figure 5, is used. V and A are,
 28 respectively, the sets of vertices and arcs. Each mode has an associated layer in this graph. Thus,
 29 $G_w = (V_w, A_w)$ is the walking layer, $G_c = (V_c, A_c)$ is the personal car layer, $G_a = (V_a, A_a)$ is the AV
 30 layer, $G_r = (V_r, A_r)$ is the train layer, $G_s = (V_s, A_s)$ is the subway layer and $G_b = (V_b, A_b)$ is the
 31 bus layer. The walk layer is based on walkable streets. The car and AV layers are based on the
 32 road network: vertices and arcs correspond to road intersections and links. The train, subway, and
 33 bus layers are based on the public transportation network: vertices and arcs correspond to transit
 34 stations and itineraries between two stations. A set of transfer arcs connect the walk layer to the
 35 other layers. Transfer arcs types are: *starter* (walk \rightarrow car), *park* (car \rightarrow walk), *pick-up* (walk \rightarrow
 36 Av), *drop-off* (AV \rightarrow walk), *board* (walk \rightarrow train, walk \rightarrow subway, walk \rightarrow bus), *alight* (train \rightarrow

#0-0	#0-1	#0-2	#0-3	#0-4 U_3
#1-0	#1-1	#1-2	#1-3 U_2	#1-4
#2-0	#2-1	#2-2 U_1	#2-3	#2-4
#3-0	#3-1	#3-2	#3-3	#3-4
#4-0	#4-1	#4-2	#4-3	#4-4

(a) Urban (in colors) and service zoning of the agglomeration.



(b) Multimodal network instance.

FIGURE 4: A theoretical urban area.

- 1 walk, subway \rightarrow walk, bus \rightarrow walk). Another set of transfer arcs of type *alighboard* are internal
- 2 to the urban public transportation network and connect the subway and bus layers.
- 3 *Travel times*
- 4 Intra-layer arcs belonging to A_c and A_a are parameterized with a mean speed. A fixed walking
- 5 speed v_w applies on all walking arcs. Travel times on all arcs in $A_c \cup A_a \cup A_w$ are deduced from
- 6 speed and distance. Each transit line is characterized by a cruising speed (v_r, v_s, v_b), a headway
- 7 (h_r, h_s, h_b) and a time lost per station (τ_r, τ_s, τ_b). The travel time between two stations of the
- 8 same transit line is the sum of time lost per stop and travel time at cruising speed. The travel time
- 9 between two stations of different transit lines located at the same coordinates is approximated to
- 10 be half the headway, such as the travel time between a walk node and a transit station with the
- 11 same coordinates. The travel times on *starter, park, drop-off, alight* arcs are considered null and,
- 12 travel times on *pick-up* arcs depend on the behavior of the AMoD but a reference pick-up time (τ_a)
- 13 is used for travelers itinerary choice.
- 14 *Travel costs*
- 15 Itinerary choice is considered deterministic and based on generalized travel costs. Travel cost
- 16 includes a monetary cost term, a travel time cost term, and a transfer penalty term. The monetary
- 17 cost associated with a car itinerary includes a distance-based cost (C_d^c), carried by the *car* arcs, and
- 18 a parking cost carried by the *park* arcs. On each *park* arcs, a certain parking capacity (K^c) and a
- 19 price (p^c) are defined.
- 20 The train pricing scheme comprises a base fare (f_0^r) and a distance-based fare (f_d^r). The
- 21 urban public transport network pricing scheme only includes a base fare ($f_0^{s,b}$) that should be paid
- 22 once at the network's entrance. The AMoD pricing scheme has been presented in section 3.1.

1 To homogenize time and money, we use several values of time depending on the activity
 2 (β_{ride} , β_{drive} , β_{wait}). In such an intermodal network, the transfer cost cannot be ignored (24).
 3 The disutility associated with transferring from one mode to another has largely been studied,
 4 particularly in transit systems (25, 26). This is taken into account through a monetized transfer
 5 penalty $\gamma_{transfer}$. An adapted version of the Dijkstra algorithm is used to account for transfer
 6 penalties while exploring the graph.

7 *Relevant willingness to wait*

8 Resulting from the itinerary choices, a set of requests is addressed to AMoD where each request
 9 has an origin, a destination ($\in V_w$), and timing constraints. A critical parameter is the maximum
 10 waiting time w_j . Here, w_j is computed following equation 7.

$$w_j = \frac{c_j^{\bar{a}} - c_j^a}{\beta_{wait}} \quad (7)$$

11 where c_j^a is the travel cost of j on the currently followed itinerary starting from the arrival node of
 12 *pick-up* edge, $c_j^{\bar{a}}$ is the travel cost of j from the origin node of *pick-up* edge to his destination on the
 13 best itinerary that does not rely on AMoD. This equation corresponds to a simple behavior: when
 14 traveler's waiting cost reaches the extra cost of not using AV during his trip, he cancels his request
 15 and diverts to this alternative itinerary. We assume that after having canceled once, a traveler will
 16 not try to use AV later in his journey: he follows the alternative path until his destination.

17 **An unfavorable scenario to challenge heuristics**

18 Finally, as we are looking to evaluate the benefits of introducing a horizon to an assignment-based
 19 heuristic, we stick to an unfavorable scenario for AMoD. By unfavorable, we mean: (i) operating
 20 within a large coverage zone, (ii) with a limited number of vehicles, (iii) during morning commute
 21 in a monocentric city. Due to (i) and (iii), more repositioning efforts are required by vehicles,
 22 especially for distant requests from the center. Due to (ii), the dispatcher has effectively choices to
 23 make between requests. Some will be prioritize to the detriment of others, and we investigate the
 24 impact of dispatching strategy on this prioritization.

25 An ideal hybrid transit system, as the one proposed by (27, 28), is chosen for this mono-
 26 centric city. It comprises two train lines, two subway lines, twelve bus lines (figure 4b).

27 The morning commute demand pattern is a many-to-one: all travelers' destinations are in
 28 the center. Regarding network topology and travel costs, most of them prefer to request AV for a
 29 door-to-door ride. A marginal part of them requests AV for the first-mile, to join a transit station.
 30 To analyse AMoD's level of service, the area is split into 25 service zones called from #0-0 to
 31 #4-4 (figure 4a). Figure 6 shows the demand-supply imbalance. In total, 4000 requests are emitted
 32 during 3 hours.

33 All parameters can be found in appendix 8.

34 **AMoD-travelers interactions**

35 AMoD and travelers interact within this environment following figure 7. A traveler j who chooses
 36 an itinerary including an AV ride sends his request to AMoD. It contains timing constraints com-
 37 puted with w_j , obtained from other transportation alternatives. The dispatcher receives requests H
 38 in advance and, in real-time, AVs states, positions, and service plannings. It resolves the optimal
 39 assignment problem and decides to match j with i . For *permanent* strategy, j is immediately added

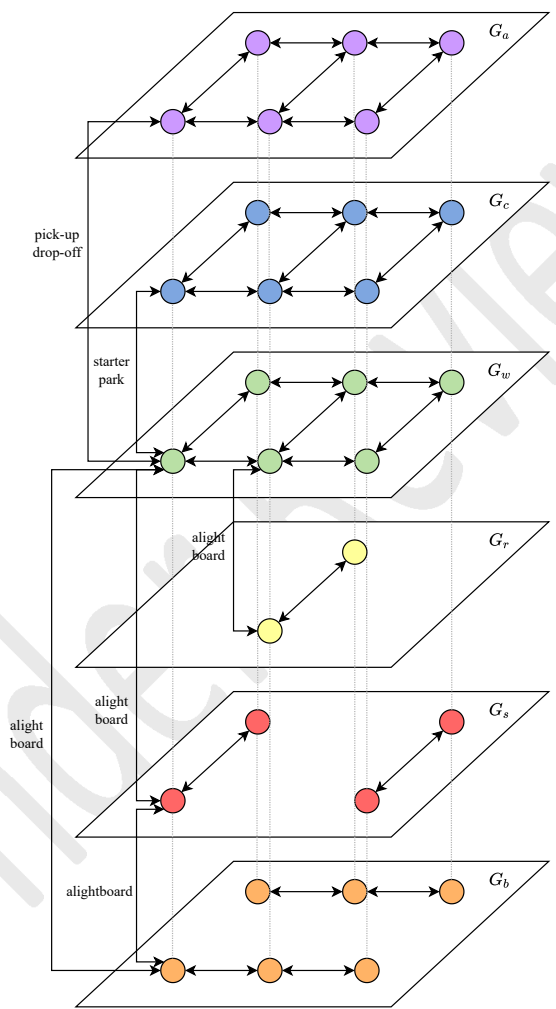


FIGURE 5: The multimodal network.

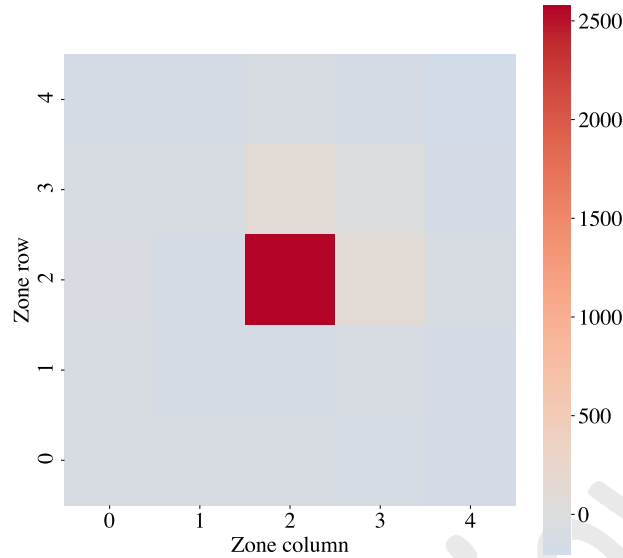


FIGURE 6: Number of pick-ups minus number of drop-offs requested per zone. A many-to-one demand pattern is considered in the theoretical instance to provoke tough imbalance between supply and demand.

1 to i 's service list. For *temporary*, if e_j belongs to the second part of the horizon, i only receives
 2 the order to reposition toward j 's pick-up point till the next assignment round. For a permanent
 3 match, j is picked-up by i as soon as i arrives, except if e_j is not yet reached. In this case, i waits
 4 for j . Then, i picks j up, carries him to his destination, and drops him off. For non-AV legs of
 5 the itinerary, customer travels node by node on the other graph layers. Travelers who have cho-
 6 sen car mode book parking in advance to prevent overcoming capacity. Behaviors are detailed in
 7 appendices 9 and 10.

8 Benefits for AMoD and travelers

9 Seven specific indicators are tracked.

- 10 • AMoD-side:
- 11 – **P**, total profit earned during the whole studied period
 - 12 – **TDTS**, total distance traveled by serving AVs
 - 13 – **TDTE**, total distance traveled by empty AVs, including AVs that are permanently
 14 matched and AVs that are temporarily matched
- 15 • Travelers-side:
- 16 – **ORR**, the order response rate, defined as the ratio between the number of matched
 17 requests and the total number of requests emitted
 - 18 – **TWT**, total waiting time for AVs, including the total realized pick-up time, the total
 19 waiting time of travelers that have canceled and, the total waiting time of travelers that
 20 are still waiting at the end of the studied period
 - 21 – **G**, the gini coefficient of zones' ORRs, it reflects the inequality of ORR among zones

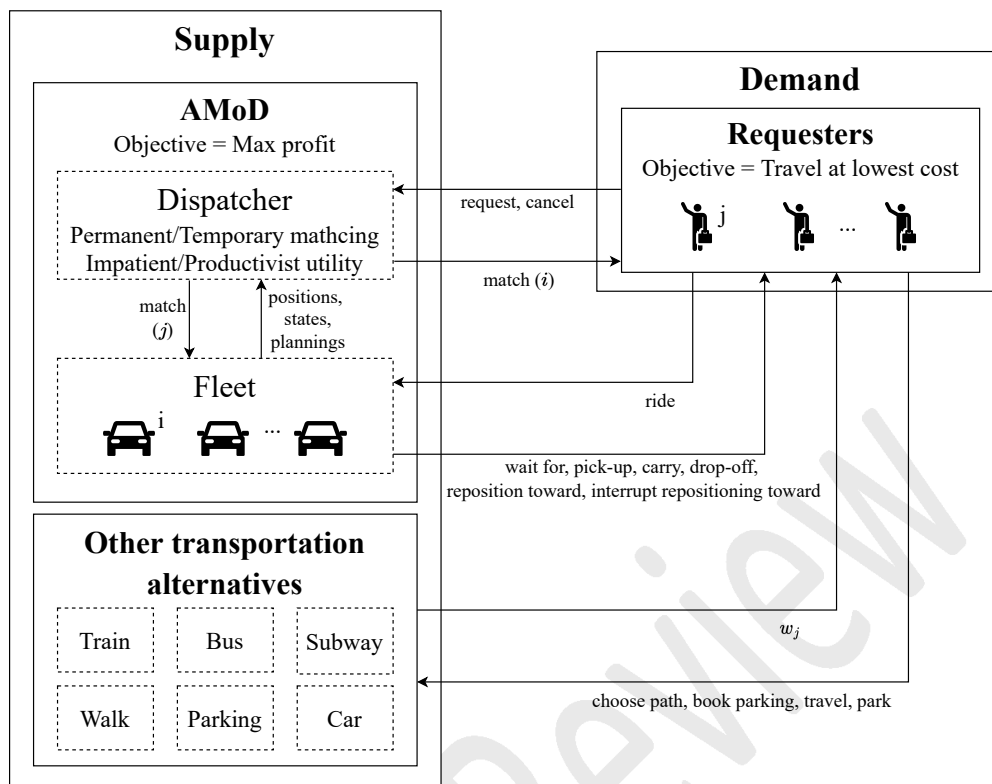


FIGURE 7: AMoD-travelers interactions.

1 RESULTS

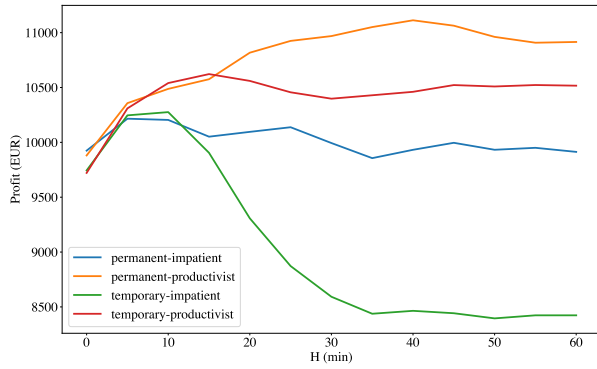
2 We present the results obtained on the instance described above.

3 Sensitivity of H on supplier and customer

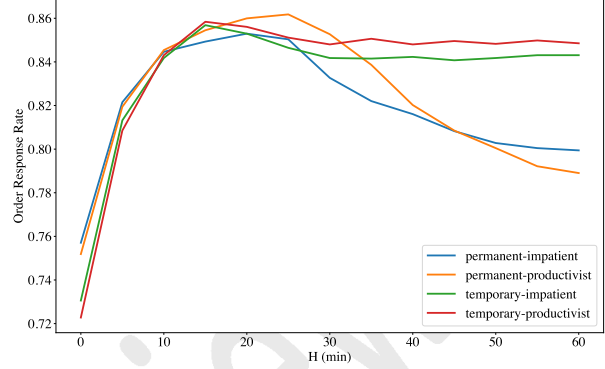
4 To better highlight differences between the proposed strategies, we let more freedom to the dis-
 5 patcher by focusing on patient requesters. In this section, all travelers have a large willingness
 6 to wait $W = 20\text{min}$. The maximum planning length K is set to 2 by default. As discussed in sec-
 7 tion 3.4, a proper value of α should be chosen. We preliminary compare $\alpha H = 5, 10\text{min}$, $H \in [0, 60]$
 8 under the four strategies. We choose to set $\alpha H = 10\text{min}$ if $H \leq 10$, and H otherwise because the
 9 variation range of simulation time is smaller with a similar number of idle AVs o, average. Our
 10 four assignment strategies are compared on their sensitivity to the horizon parameter H . Results
 11 are represented on figure 8.

12 *Introduction of a horizon enables AMoD to serve more requests whatever the strategy*

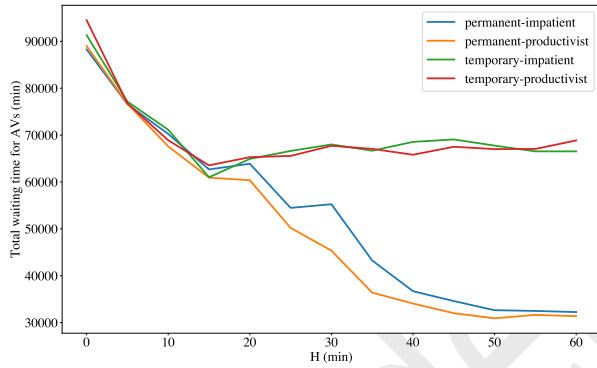
13 ORR starts by increasing with H . The fleet is underused at $H = 0$, with at least a hundred AVs
 14 being idle at any time. The lack of anticipation prevents AVs from being dispatched to distant
 15 requests. The repositioning time required to join pick-up points of corner zones (#0-0, #0-4, #4-0,
 16 #4-4) from #2-2 (where most AVs finish their service mission), is higher than W . Consequently,
 17 inequalities in ORR among zones are significant, as shown in figure 9a and confirmed by G, above
 18 0.2 for all strategies.



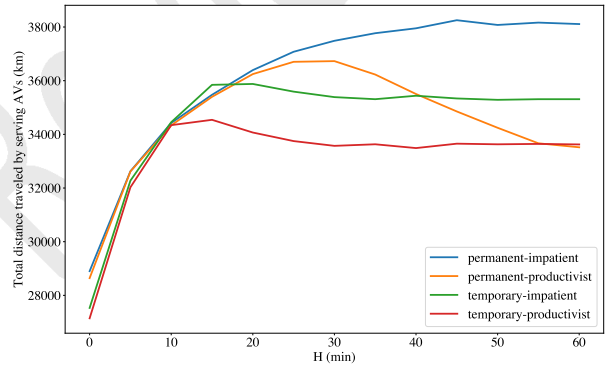
(a) P



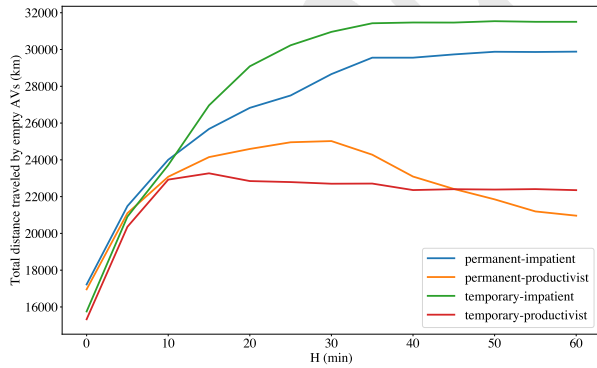
(b) ORR



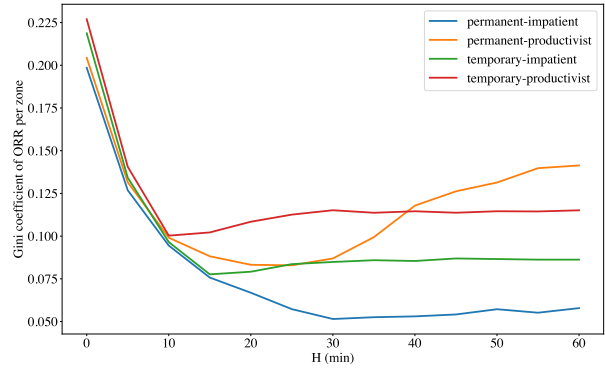
(c) TWT



(d) TDTS



(e) TDTE



(f) G

FIGURE 8: Sensitivity of H on metrics for the four dispatching strategies.

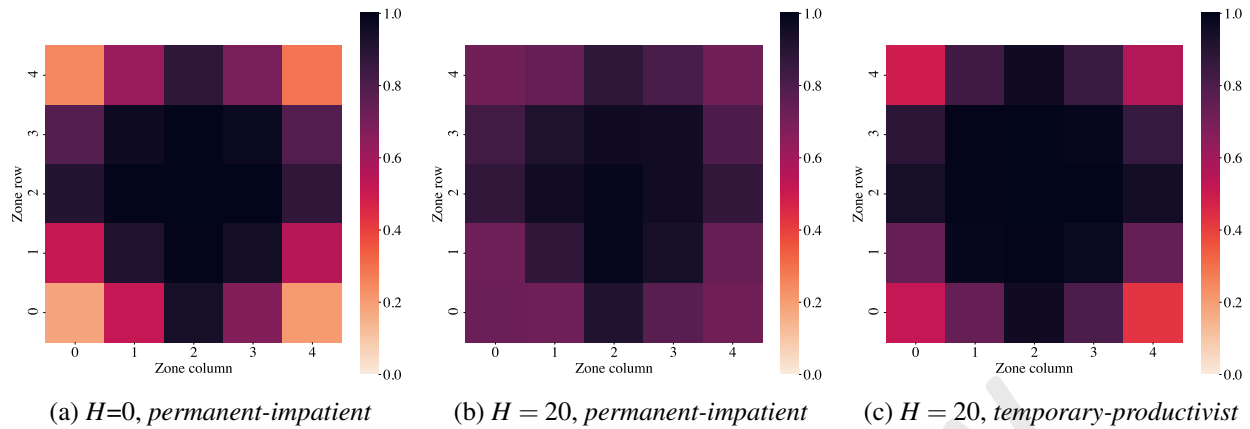


FIGURE 9: ORR per zone.

- 1 *The productivist strategies are better to maximize ORR, to the detriment of G*
- 2 A horizon of 15-25min maximizes the number of matches. The maximal value of ORR reached
- 3 depends on the strategy. The *productivist* are better than *impatient*. In parallel, G decreases but not
- 4 to the same extent for the four strategies. The *impatient* utilities erase more ORR disparities than
- 5 *productivist* ones. Figures 9b and 9c represent the ORR per zone at $H = 20$ for the two extreme
- 6 strategies in terms of G. With the same knowledge of future requests, the improvement of ORR in
- 7 U_3 corner zones is better for *permanent-impatient*.
- 8 *Two distinct behaviors emerge from the two utilities*
- 9 For *permanent-impatient*, distant requests for which AVs can arrive just in time are more attrac-
- 10 tive than closer requests for which AVs would have to wait for the customer. For *temporary-*
- 11 *productivist*, distant requests prior notices are not convincing, and AMoD prefers to dispatch AVs
- 12 to closer customers. Similarly, for *permanent-productivist*, AVs are matched in priority with closer
- 13 requests even if they must wait for the customer. AV waiting time is included in $u_{ij}^{productivist}$ defi-
- 14 nition, contributing to the time required to earn a certain profit. But it does not have as much im-
- 15 portance as in the *impatient* utility. The average number of waiting AVs for $H = 20$ in *permanent-*
- 16 *productivist* has a higher score (50 AVs) than in the other three (around 20 AVs). For *temporary-*
- 17 *productivist*, we do not find a consequent number since only AVs waiting for a customer involved
- 18 in a permanent match are counted.
- 19 *Extending knowledge even more has no effect for temporary strategies*
- 20 The decreasing phase with H higher than 15-25min does not affect the four strategies similarly. The
- 21 *temporary* ones are less impacted, with a slight decrease in the number of matches and early stabi-
- 22 lization of metrics. Providing more information to the dispatcher does not change fleet's behavior.
- 23 The dispatcher has exploited the maximum amount of information possible. The additional notices
- 24 included within the horizon are candidates for repositioning in the *temporary* strategies. Yet, only
- 25 idle AVs are likely to be temporarily matched with a candidate for repositioning. Since fleet is not
- 26 oversized, most AVs are occupied with a service mission at each instant. No supplementary idle
- 27 AV is available for being matched with the additional prior notices. The value of H from which
- 28 stabilization happens depends mainly on fleet size (oversupply allows to keep more AVs available

1 for repositioning missions) and K (longer planning may free some AVs by loading AVs' schedules
2 more).

3
4 For *permanent* strategies, we do not observe the same stabilization when H increases over
5 $H = 25$. From $H = 25$, *permanent-impatient* loses 200 matches and *permanent-productivist*
6 loses 280 matches.

7 *With permanent-productivist, extending H too much favours AMoD and puts customers at a disad-*
8 *vantage*

9 We find that for $H \geq 25$, TDTS and TDTE decrease at the same pace. AVs serve fewer travelers,
10 provide less repositioning effort and serve fewer kilometers. In parallel, G reaches its minimum at
11 $H = 25$ and then increases. AMoD is more focused on central zones and serve shorter and closer
12 requests. Extending the horizon makes more of these requests visible to the AMoD, and AVs that
13 were sent in U_3 are kept in U_1 instead. As more and more AVs desert U_3 to wait for new customers
14 in U_1 and U_2 , the number of matches decreases. The average number of waiting AVs doubles
15 between $H = 20$ and $H = 60$.

16 Meanwhile, P increases until $H = 40$, when the maximum profit score is reached (11112
17 EUR). By focusing more on shorter and closer requests while ignoring more distant and longer
18 requests, AMoD's profit increases until the time lost due to AVs arriving ahead of time becomes
19 disadvantageous.

20 *Anticipating too much is negative for ORR but dummy for G and P with permanent-impatient*

21 Both TDTS and TDTE grow at the same pace. AVs serve fewer customers but make more repositioning
22 efforts for longer rides. The time to achieve a mission, from repositioning to drop-off, is
23 greater, and AVs are monopolized longer for a given mission. Moreover, the number of requests
24 candidates for a match increases with a wider horizon. Match being permanent, more AVs are nec-
25 essary to answer a batch of requests. The average number of idle AVs decreases from 40 at $H = 25$
26 to 20 at $H = 60$. By over-anticipating, *permanent-impatient* AMoD behaves too impatiently to
27 be able to maintain global ORR. It assigns AVs with distant requests that have an earliest pick-up
28 time in far future but requiring enough repositioning effort to allow the just-in-time arrival of AV
29 at the pick-up point. These far requests, being associated with longer rides, are profitable enough
30 to be prioritized by the optimal assignment method. Increasing K jointly with H may absorb, to
31 some extent, the reduction of global ORR by making AVs currently monopolized by long rides,
32 available to receive more service mission orders. In figures 10, we effectively have more matches
33 when $K = 3$ but, within the same simulated duration, it does not mean higher TDTS. At the end
34 of the studied period, we have more AVs that have not finished their service missions. At $H = 60$,
35 TDTS of both scenarios join. This confirms that within a 0-60min range for the horizon, 2 is a
36 proper value for the planning length.

37 A wider horizon does not negatively impact P nor G . P variation range is quite narrow
38 (9856-10215 EUR) since TDTS and TDTE increase jointly: repositioning efforts and service dis-
39 tance benefits are balanced. G maintains from $H = 30$.

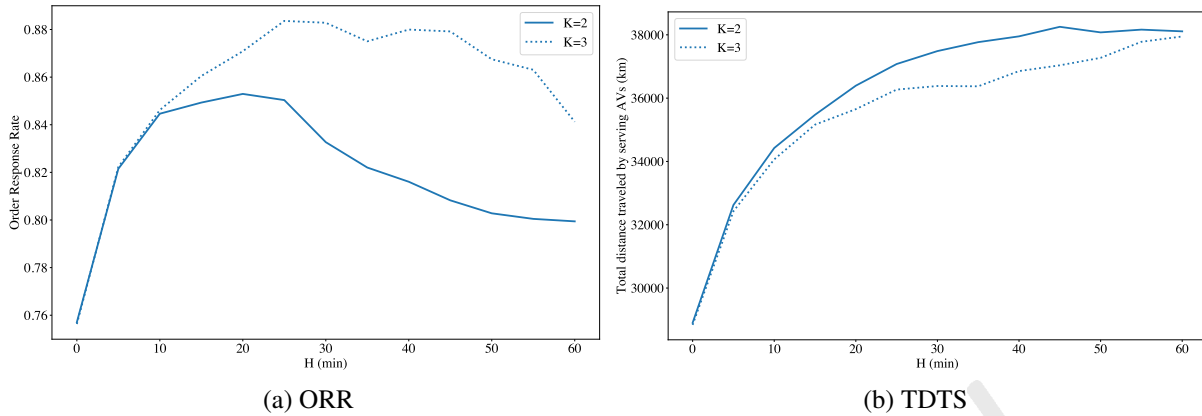


FIGURE 10: Comparison of sensitivities to H for $K = 2$ and $K = 3$ for the *permanent-impatient* strategy.

1 *The temporary-impatient strategy is the worse for profit due to unproductive repositioning*
 2 For *temporary-impatient*, we notice that TDTE keeps increasing while TDTs follows ORR from
 3 $H = 15$. AVs are making more repositioning efforts without any reward in terms of TDTs. More-
 4 over, counting the average number of idle AVs shows that more AVs are running (serving or repositioning)
 5 during the simulation. Consequently, the profit curve is the worst among all strategies,
 6 reaching a minimum of 8395 EUR. A temporary match with a distant request requires more than
 7 αH (10min) to be achieved. Then, it is put back into play and is exposed to interruption. Around
 8 70-80% of repositioning missions are interrupted. The repositioning AV is either permanently
 9 matched with another request than its previous target or assigned another repositioning target. The
 10 *temporary* strategy is at the origin of unproductive repositioning and, sub-optimality in dispatching
 11 decisions here. When demand prediction is not exact, it may improve system's flexibility.

12 *Repositioning in temporary-productivist is more flourishing and leads to a satisfying and stable P*
 13 *for supplier but higher spatial disparities in ORR*
 14 For *temporary-productivist*, TDTs, TDTE and P are similar to *permanent-productivist* until $H =$
 15 15. From then, the three indicators and G stabilize, letting this strategy below *permanent-productivist*
 16 in terms of P. The maximal profit reached is the second best (10622 EUR). We note that using the
 17 *productivist* utility rather than the *impatient* one, allows to reach a higher ratio of repositioning
 18 missions achieved (70-80%). Indeed, the repositioning missions are shorter so have less occasions
 19 to be interrupted.

20 *The permanent strategies are better for improving TWT and mean realized pick-up time as H*
 21 *increases*

22 The *permanent* strategies have similar monotonically decreasing TWT profiles. Regarding the total
 23 realized pick-up time, it reduces as H increases. The mean realized pick-up time starts around
 24 12min for $H = 0$ and reaches 2min at $H = 60$ for both strategies. If the number of matches
 25 decreases, the quality of service for matched travelers largely increases.

26 The *temporary* strategies also have similar TWT profiles: it starts by decreasing, then sta-
 27 bilizes just as other indicators. The mean realized pick-up time variation range is narrow, reaching

1 9min for $H = 15$ and remaining around 12min for shorter and wider horizon.

2

3 The advantage of *productivist* utility for the supplier is evident here: waiting passively in
 4 the center is a more profitable strategy for AMoD compared to actively looking for more distant
 5 rides. This behavior is the origin of deeper disparities in terms of ORR (G).

6 **Extension to traveler-specific willingness to wait**

7 In this section, we wonder how strategies adapt to more impatient travelers. We also go further in
 8 the analysis of travelers-side indicators.

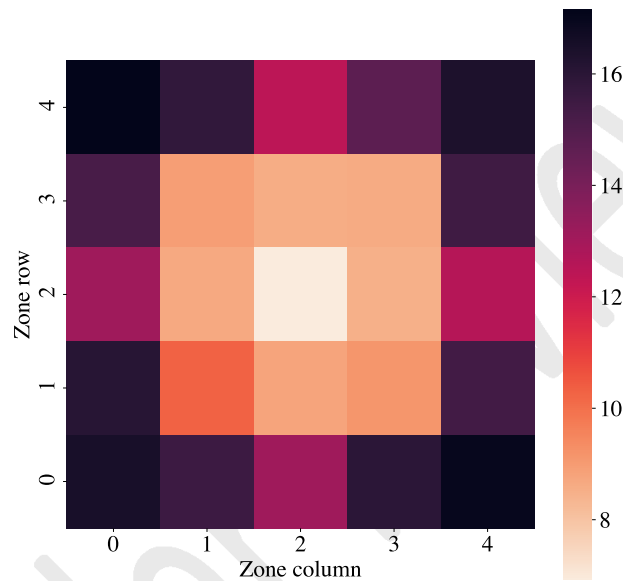


FIGURE 11: Mean maximum waiting time per zone.

9 When the maximum waiting time is not constant but based on available alternatives on
 10 the transportation network, it becomes traveler-specific. Figure 11 represents the mean maximum
 11 waiting time per zone. It shows smaller values in zones better supplied by transit. Travelers who
 12 emit a request from a corner zone of U_3 are more willing to wait (16min) than travelers who emit a
 13 request from the central zone (7min). The more traveler is willing to wait, the more he depends on
 14 AVs. Here, we investigate the inequalities in terms of quality of service, represented by the realized
 15 pick-up time. We wonder if inequalities in quality of service are related to AV-dependency and to
 16 what extent. As *permanent* strategies have performed better than *temporary* strategies for both
 17 utilities (in terms of P, ORR, TWT), we select them for this analysis.

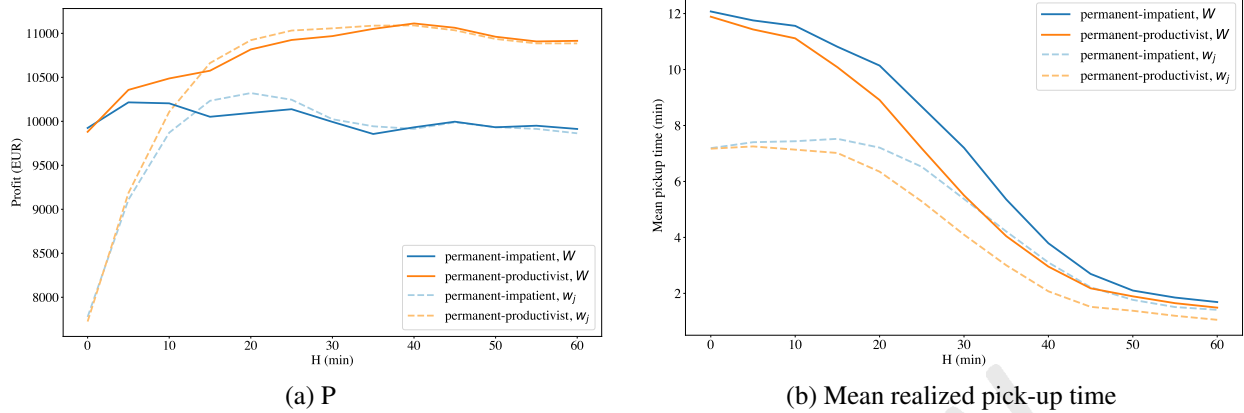


FIGURE 12: Sensitivity of H with constant (W) and traveler-specific (w_j) maximum waiting time.

1 Figure 12b shows that mean realized pick-up time is always lower in the traveler-specific
 2 maximum waiting time scenario (w_j). It is consistent since travelers are more demanding ($w_j \leq W$).
 3 The difference in mean realized pick-up time with W scenario reduces as H increases. Figure 12a
 4 shows that with a short horizon, AMoD does not succeed in answering as many requests as in the
 5 W . When anticipation is sufficient, all indicators of w_j scenario (except TWT) join those of W
 6 scenario. It demonstrates the resilience of the *permanent* anticipative heuristics proposed under
 7 tougher timing constraints.

8 Figure 13 presents the concentration curves (29) for quality of service. To obtain it, we
 9 have defined five classes of AV-dependency from the less dependent to the most:

- 10 1. $w_j \leq 7$
- 11 2. $8 \leq w_j \leq 10$
- 12 3. $11 \leq w_j \leq 13$
- 13 4. $14 \leq w_j \leq 16$
- 14 5. $17 \leq w_j$

15 On the x-axis, it plots the cumulative proportion of travelers (all on 13a, only those that have been
 16 matched on 13b), beginning with the less AV-dependent, ending with the most AV-dependent.
 17 On the y-axis of figure 13a (resp. figure 13b), it plots the cumulative share of travelers being
 18 matched (resp. of total waiting time). If matches (resp. waiting times) are equally undergone
 19 across classes, the concentration curve would coincide with the diagonal. The degree of inequality
 20 can be represented by the concentration index C_i , which equals 0 for perfect equality. It is worth -1
 21 (resp. 1) for a perfect inequality to the disadvantage of the less AV-dependent, i.e., all matches are
 22 attributed to the less AV-dependent (resp. the most AV-dependent travelers undergo all the waiting
 23 time imposed by AMoD). Here, computing c_i and looking at the curves indicates that:

- 24 • $C_i(\text{matches}, \text{impatient}) = -0.015$
- 25 • $C_i(\text{waitingtimes}, \text{impatient}) = 0.093$
- 26 • $C_i(\text{matches}, \text{productivist}) = -0.088$
- 27 • $C_i(\text{waitingtimes}, \text{productivist}) = 0.180$
- 28 • *productivist* favors the less AV-dependent travelers in terms of matches and pick-up time
 29 more than *impatient*
- 30 • with *productivist*, the 50% of travelers the less AV-dependent attract 60% of the matches

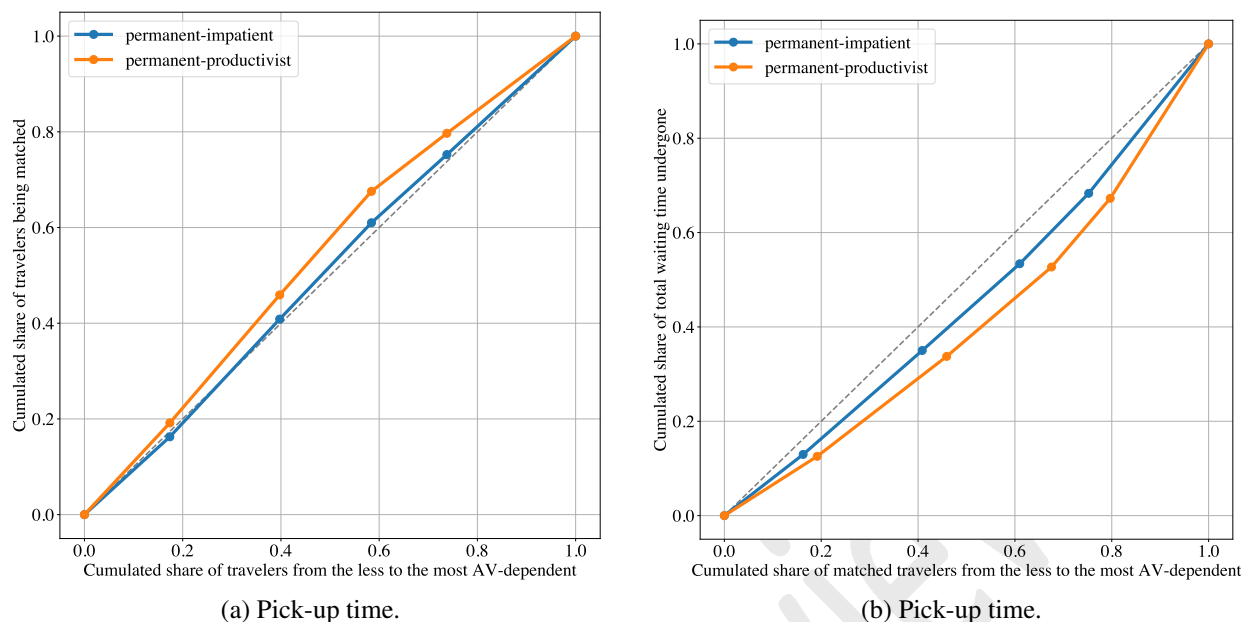


FIGURE 13: Concentration curves for quality of service related to AV-dependency.

- 1 • with *productivist*, the 20% of matched travelers the most AV-dependent undergo 1/3 of
- 2 the total realized pick-up time while the 20% of matched travelers the less AV-dependent
- 3 undergo 12% of this quantity

4 Comparison with heuristic

5 We have shown that a horizon helps improve AMoD-side and travelers-side benefits. Yet, we have
 6 stuck to a slightly undersized fleet. In this section, we compare our anticipative assignment-based
 7 approach with the rule-based heuristic presented in section 3.5 for undersized and oversized fleets.
 8 We still focus on *permanent* strategies and, set H to 25min (where ORR is maximal for both
 9 *permanent* strategies). Figure 14 present the results for a traveler-specific maximum waiting time.

10 The (rule-based) *heuristic* strategy is less sensible to fleet size than *permanent* in terms of
 11 ORR and P. There are more and more idle AVs that do not succeed in answering the remaining
 12 unmatched requests. In our unfavorable instance, the lack of anticipation prevents idle vehicles,
 13 mostly located in the central zone, from satisfying timing constraints of corner zones' requests.
 14 The horizon allows the other two strategies to take advantage of supplementary resources: ORR
 15 keeps increasing till the maximum fleet size. On average, for 600 AVs, there are 380 idle AVs with
 16 the *heuristic* strategy, 80 with the *permanent-impatient* and, 75 with the *permanent-productivist*.
 17 The ORR (resp. P) gap is around 0.45 (resp. 4000 EUR). Note also that as fleet size increases, the
 18 gap between *impatient* and *productivist* strategies narrows.

19 Regarding G , *heuristic* remains around 0.2-0.3 which is better than *permanent-productivist*
 20 for a fleet containing less than 350 AVs, but worse for greater fleets. The tendency to focus on less
 21 distant and shorter rides highlighted for *permanent-productivist* is close to what *heuristic* emulates.
 22 For assignment-based heuristics, when more AVs are available, ORRs of corner zones increase, and
 23 G is almost null, as shown in figure 15.

24 Regarding mean realized pick-up time, *heuristic* and *permanent-impatient* have similar

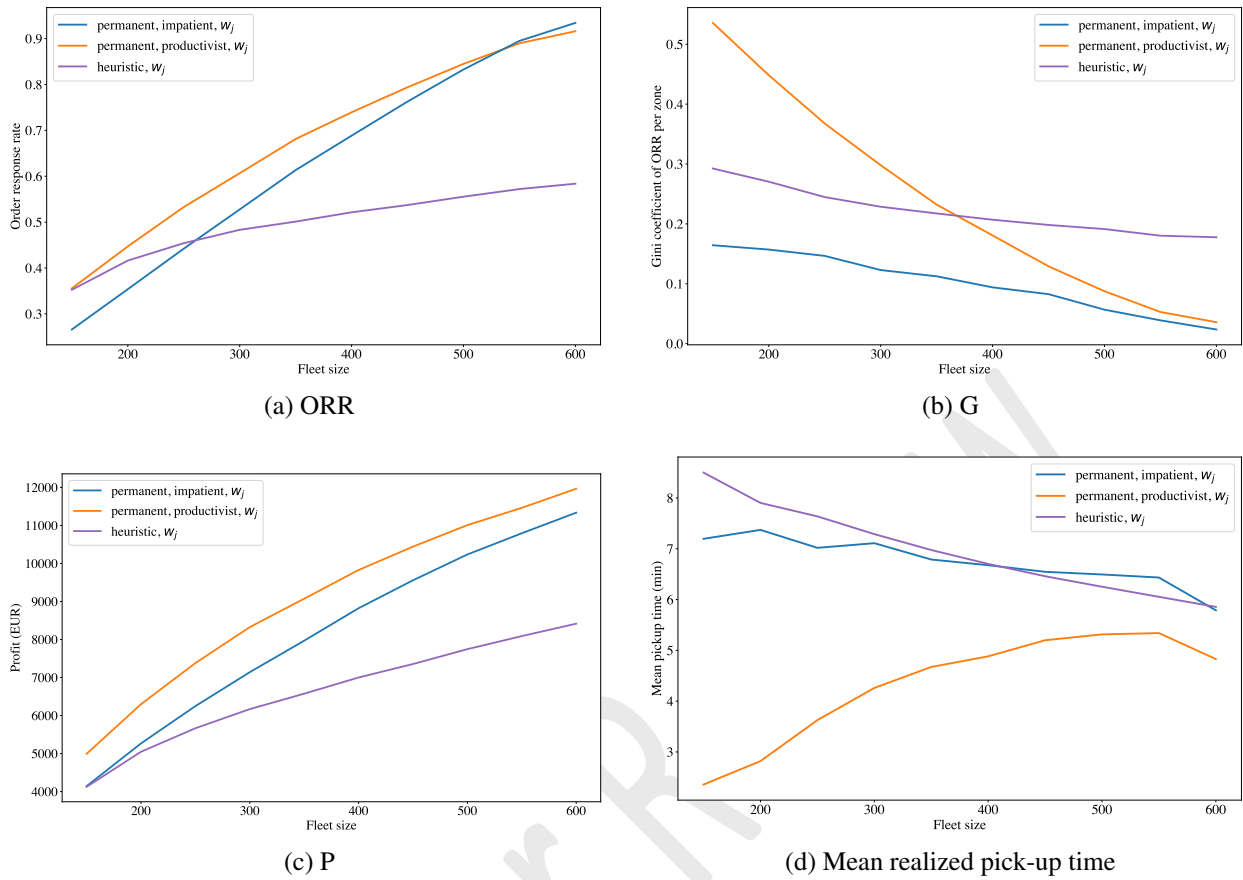


FIGURE 14: Sensitivity of fleet size for *permanent* and *heuristic* strategies with traveler-specific (w_j) maximum waiting time ($H = 25$)

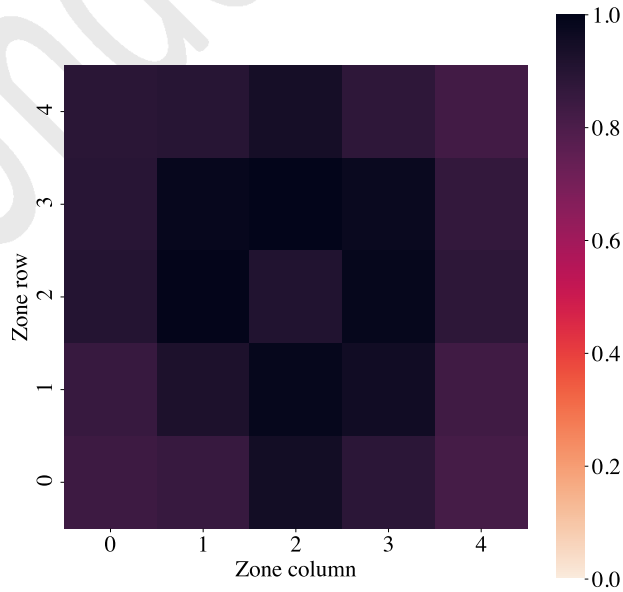


FIGURE 15: ORR per zone for *permanent-productivist* strategy with 600 AVs ($H=25$).

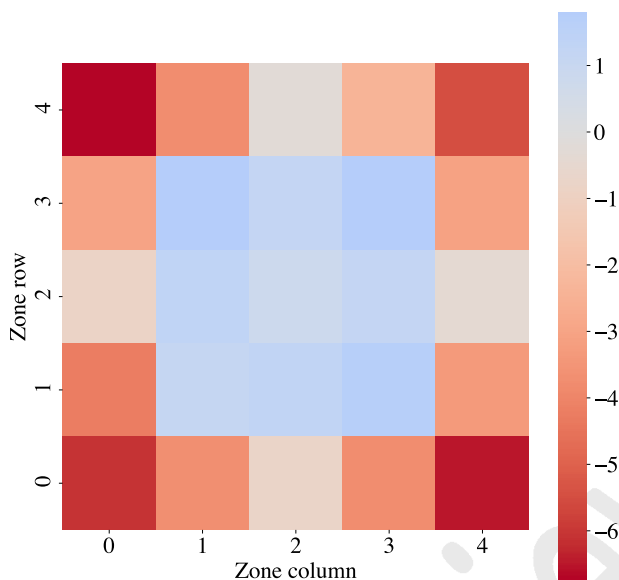


FIGURE 16: PSC1 where prices are positive and subsidies are negative (EUR).

1 decreasing profiles. In the case of *heuristic*, it decreases from 8min for 150 AVs to 6min for 600
 2 Avs, but this is at the price of numerous idle AVs. The *permanent-productivist* strategy is better
 3 than the other two, with a variation range extending from 3min to 5.5min.

4 **Inclusion of a regulator**

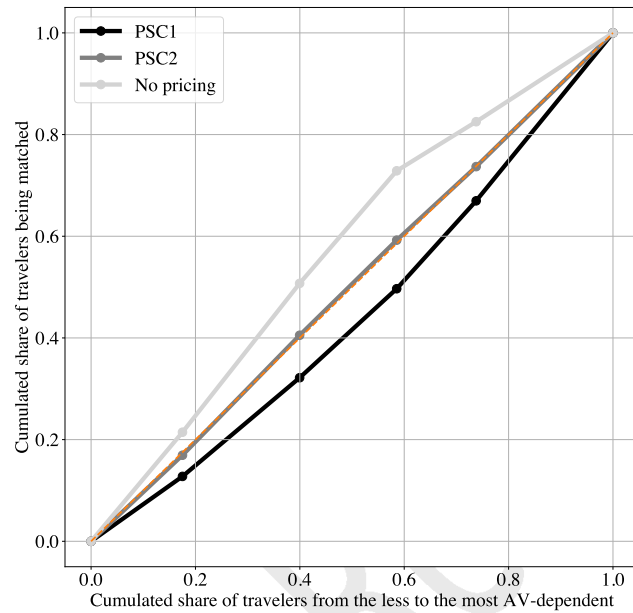
5 As highlighted above, *permanent-productivist* is the strategy maximizing the profit of AMoD, but
 6 it does to the detriment of equity among travelers under a limited fleet size. In this section, we add
 7 a regulator stakeholder in the system. It aims at restoring equity under this strategy by setting up a
 8 pick-up pricing scheme. We test two intuitive pricing schemes:

- 9 • **PSC1:** Subsidies are attributed to AVs for picking up a traveler in an AV-dependent
 10 zone, and prices are imposed on AVs for picking up a traveler in a non-AV-dependent
 11 zone. Subsidies and prices are proportional to: (i) the AV-dependency of the zone, (ii)
 12 the distance of this zone from the center of the city. Figure 16 shows prices per zone.
- 13 • **PSC2:** Subsidies are the same as in PSC1, but there are no prices.

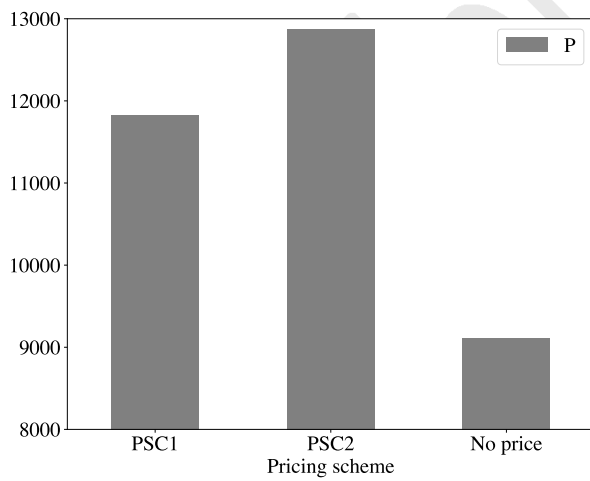
14 Figure 17 shows that compared to no pick-up price scenario, PSC2 reaches equality in
 15 terms of matches while PSC1 brings equity. In the latter scenario, the 40% travelers more AV-
 16 dependent get 50% of the matches. Due to the definition of schemes providing more subsidies
 17 than collecting prices, P increases by 2715 EUR with PSC1 and by 3757 EUR with PSC2. As
 18 expected, ORR slightly decreases.

19 **CONCLUSION**

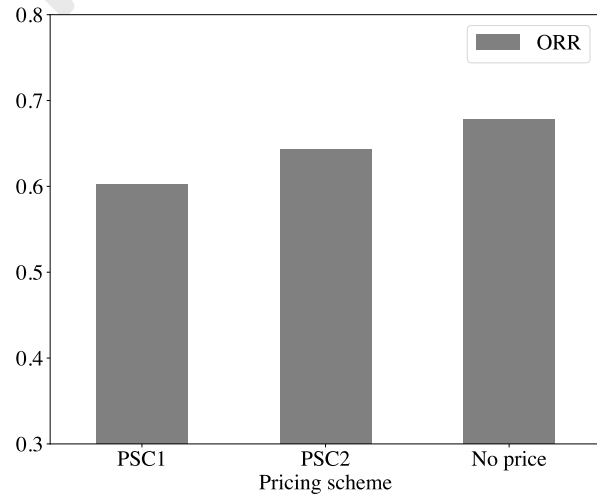
20 In this study, we have investigated the effect of demand prediction horizon on AMoD-side and
 21 travelers-side indicators for an assignment-based dispatching heuristic. We have tested four strate-
 22 gies and analyzed the sensitivity of each to horizon length in an unfavorable theoretical environ-
 23 nment. Introducing a short/mid-term horizon (5-25min) allows AMoD to increase its profit by
 24 serving more requests, improves the mean realized pick-up time for travelers and reduces spatial
 25 disparities in terms of ORR. For *temporary* mode, extending more the horizon does not change



(a) Concentration curves for the three pricing schemes



(b) P



(c) ORR

FIGURE 17: Effect of pricing schemes for *permanent-productivist* ($w_j, H = 25, 350$ AVs)

1 travelers' outcomes but degrades AMoD's profit in case of unproductive repositioning, as it hap-
2 pens in *temporary-impatient* strategy. For *permanent* mode, anticipating long-term requests de-
3 grades ORR. Two distinct behaviors emerge depending on the strategy. With an *impatient* utility,
4 AVs are rewarded for making more repositioning efforts and maintain a good profit level for higher
5 horizon lengths. With a *productivist* utility, AVs succeed in earning more profit by waiting for fu-
6 ture customers in the center. Comparison with a non-anticipative heuristic has shown the ability
7 of our dispatching to exploit supplementary vehicles. Even when fleet is oversized, a severe im-
8 balance between supply and demand prevents the rule-based heuristic from performing similarly.
9 The *permanent-productivist* maximizes AMoD's profit but worsen spatial inequalities. Especially,
10 the most AV-dependent travelers are less matched. Those who are matched undergo a bigger part
11 of the total waiting time compared to the least AV-dependent. One pricing scheme for restoring
12 equality and another for advantaging the most AV-dependent have been proposed.

13 Our study can be extended in several ways. A real-world instance would be a more nuanced
14 scenario to test our dispatching strategies. Removing the monocentric hypothesis, the many-to-one
15 filter would lead to a lighter imbalance between supply and demand and may highlight new behav-
16 iors. Considering the entire demand on a real agglomeration would enable us to perform a simu-
17 lation time analysis and check the scalability of the approach. Finally, we could go further on de-
18 signing pricing schemes that benefit AMoD, travelers and regulator. For example, prices/subsidies
19 could be passed on AVs and travelers jointly to change AMoD usage from a majority of door-to-
20 door rides to more first/last-mile rides.

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1 THEORETICAL INSTANCE PARAMETERS

2 Road network

v_{U_1}	0.55	(m/s)	Mean speed in U_1
v_{U_2}	0.67	(m/s)	Mean speed in U_2
v_{U_3}	1.17	(m/s)	Mean speed in U_3
$v_{U_{12}}$	1.09	(m/s)	Mean speed on U_{12} ring road
$v_{U_{23}}$	1.34	(m/s)	Mean speed on U_{23} ring road
C_d^c	0.6	(EUR/km)	Operation cost of personal car
ρ_{U_1}	50	%	Probability of free private parking in U_1
$p_{U_1}^c$	6	(EUR)	Parking price in U_1
$K_{U_1}^c$	10	(parking spots)	Number of parking spots per <i>park</i> edge in U_1

3 Transit

v_r	1.34	(m/s)	Cruising speed of train
τ_r	2	(min)	Time lost per station for train
h_r	15	(min)	Headway of train lines
f_0^r	0.5	(EUR)	Base fare for train
f_d^r	0.2	(EUR/km)	Distance-based fare for train
v_s	0.9	(m/s)	Cruising speed of subway
τ_s	1	(min)	Time lost per station for subway
h_s	4	(min)	Headway of subway lines
v_b	0.55	(m/s)	Cruising speed of bus
τ_s	1.5	(min)	Time lost per station for bus
h_s	6	(min)	Headway of bus lines
$f_0^{b,s}$	1.5	(EUR)	Fare for entering transit network
v_w	0.11	(m/s)	Walking speed

4 AMoD

f_0^a	1.3	(EUR)	Base fare for AMoD
f_d^a	0.3	(EUR/km)	Distance-based fare for AMoD
f_t^a	0.3	(EUR/min)	Time-based fare for AMoD
C_d^a	0.27	(EUR/km)	Operation cost of AV
τ_a	5	(min)	Reference pick-up time

5 Travelers

β_{wait}	0.425	(EUR/min)	Value of time when waiting
β_{ride}	0.17	(EUR/min)	Value of time when riding transit of AV
β_{drive}	0.255	(EUR/min)	Value of time when driving
$\gamma_{transfer}$	0.85	(EUR)	Transfer penalty

1 TRAVELER BEHAVIOR

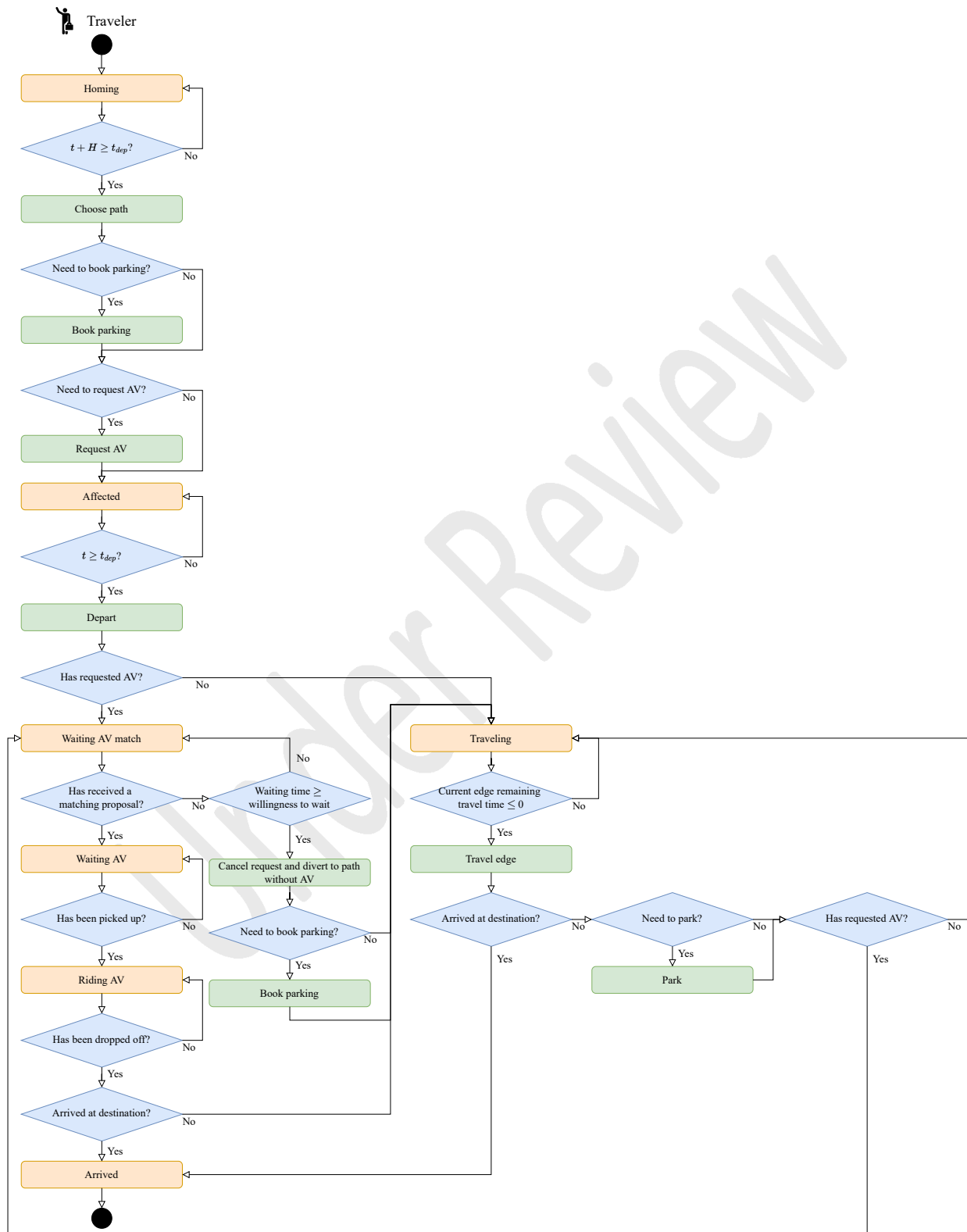


FIGURE 18: Flow chart of traveler.

1 AV BEHAVIOR

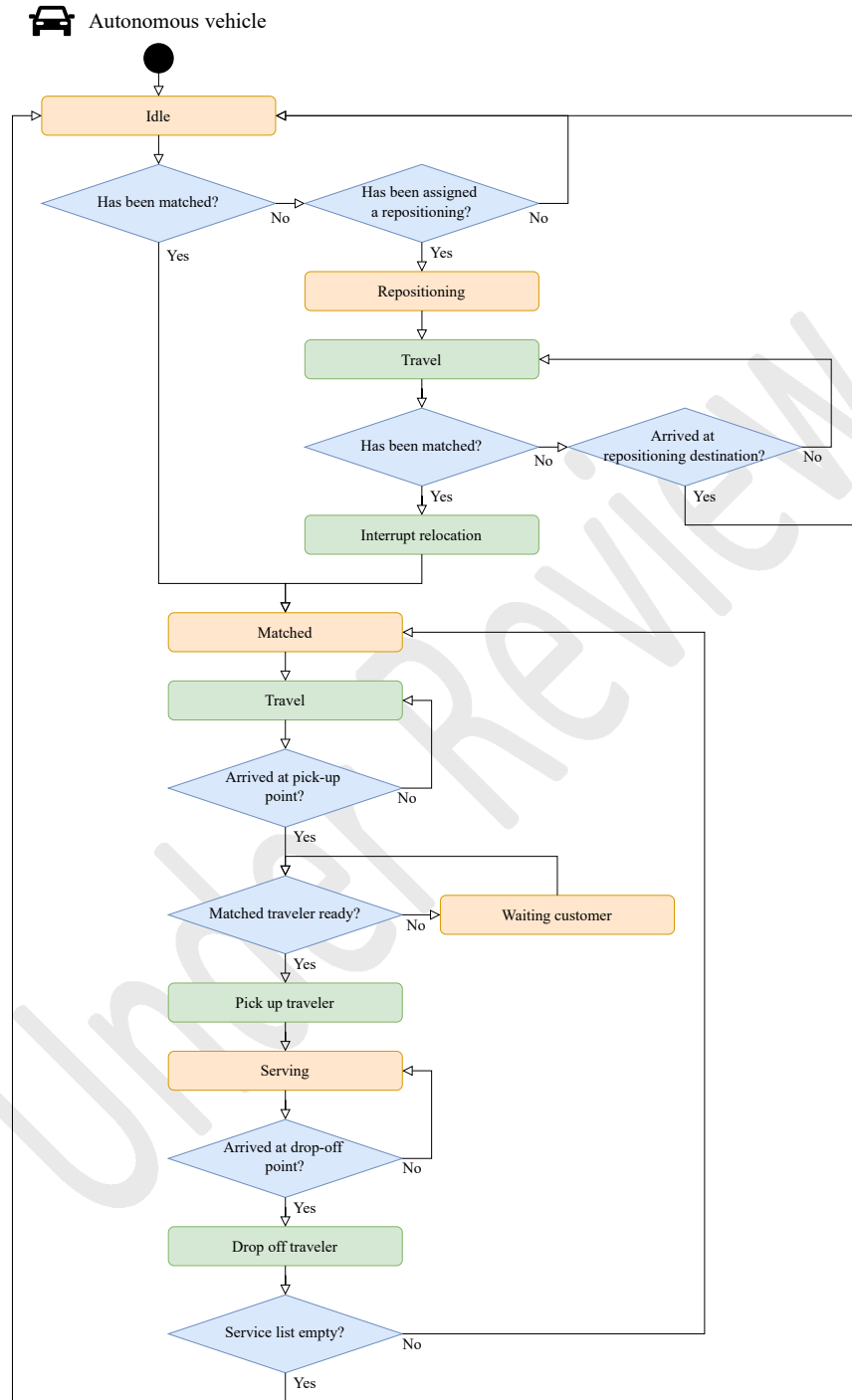


FIGURE 19: Flow chart of AV.