

Agent-based Modeling for Dynamic Hitchhiking Simulation and Optimization

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Abstract: Although many new transportation services have emerged, hitchhiking continues to be popular, especially in rural areas. In the last 10 years, many countries have tried to encourage and revitalize this mode of transport for its ecological and social aspects. The objective is then to develop tools to ensure the connection of the users as well as the optimization of their journey while respecting the dynamic and volatile character of hitchhiking. In this perspective, we propose the Realtime Trip Availability Graph (ReTAG) approach. This approach consists of a recursive algorithm to identify and filter the relevant drivers for the riders. This algorithm generates a graph that allows the riders to establish a perception of the set of rideshares that are eligible and profitable to their situation. We establish a multi-agent system to describe the behavior and interactions of hitchhikers and drivers. We propose a comparative study of two hitchhiker behaviors. The first one simulating the behavior of a real hitchhiker, i.e. without any knowledge of his environment. The second one simulating a hitchhiker connected to an information system, and thus with knowledge of a part of the environment. We compare these two behaviors on more or less challenging problem instances in order to have a panel of convincing results. We conclude that the connected hitchhiker is superior to the real hitchhiker on a set of indicators such as the waiting time and the instance resolution speed.

1 INTRODUCTION

In this article, we focus on a special case of the dynamic ridesharing problem: hitchhiking. This type of ridesharing is still widely used in the world as a travel experience or by necessity. It is characterized by the complete absence of any prediction or reservation of a ride for the rider and, in general, by the lack of detours by the drivers. These strong characteristics make this mean of transport much less efficient than other ridesharing solutions due to a lack of communication of information between users. However, it has the advantage that it can be optimized at any time and is independent of its scale of use, making hitchhiking fully dynamic and generic.

The lack of driver detours prevents, in most cases, the possibility for a rider to rideshare with a single driver, i.e. to do a single hop ridesharing (Agatz et al., 2011) (Herbawi and Weber, 2012b). This issue leads to the need for a rider to transfer between different

drivers to advance in his journey, i.e to do a multi-hop ridesharing. Multi-hop ridesharing expands the transportation offer by making it possible to share trips that would be unfeasible with a single vehicle (Coltin and Veloso, 2014). In addition, this variant of ridesharing reduces rider waiting time and travel time (Herbawi and Weber, 2012a) (Xu et al., 2020).

However, the introduction of transfers involves identifying the most optimal combination of many possible drivers and transfer nodes. This operation involves an increased complexity. In consequence, different researchers proposed space reduction methods to limit the exploration of the numerous possibilities. A first approach is the abstraction of space. This abstraction can be done by dividing the space into zones (Nourinejad and Roorda, 2016), by selecting pickup and delivery stations (Di Febbraro et al., 2013) or by partitioning roads according to their importance (Pelzer et al., 2015). In these papers, the abstraction of space is empirical and globalizing. Alternatively, individualizing approaches propose the use of agents to design a limited and proper perception of the environment to each user of a ridesharing system. This alternative approach allows to limit the search

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space of a rider dynamically and according to his constraints and preferences. This perception is notably modeled by a transfer graph in (Jeribi et al., 2011a). This article studies ridesharing in a multi-modal context (public transport, self-service car) and proposes a graph referencing the different means of transport accessible to the rider as well as the possible transfers between these means of transport. We have chosen to extend the scope of this transfer graph to the hitchhiking problem in our paper. Indeed, its dynamic and generic character corresponds to the hitchhiking problem in which the optimization is continuous throughout the rider's journey. Moreover, the hitchhiking framework can be naturally represented by a multi-agent system since drivers and riders are autonomous entities in interaction. Multi-agent systems have been shown to be efficient for the simulation and resolution of several ridesharing variants such as taxi fleet management (Mathieu and Nongaillard, 2018), vehicle sharing services (Jeribi et al., 2011b) and ridesharing optimization with professional (Xu et al., 2020) or private drivers (Fevre et al., 2021). We therefore propose to simulate road traffic and hitchhikers as agents.

In summary, the contributions of this paper are: (1)We formalize the hitchhiking problem using a graph abstraction. (2)We define a multi-agent system modeling drivers, hitchhikers and their communications. (3)We propose a comparative study of two hitchhiker behaviors. The first one simulating the behavior of a real hitchhiker, i.e. without any knowledge of his environment. The second one simulating a hitchhiker connected to an information system, and thus with knowledge of a part of the environment. (4)We develop the Realtime Trip Availability Graph Approach that uses a recursive algorithm to generate a graph of admissible solutions for a hitchhiker.

The reminder of this paper is organized as follows. The hitchhiking problem is formulated in the section 2. Section 3 describes the suggested multi-agent architecture. The Realtime Trip Availability Graph Approach is described in section 4. Section 5 presents an evaluation of our approach. Finally, conclusion and prospects are addressed in section 6.

2 PROBLEM FORMULATION

2.1 Definition of an Instance of the Dynamic Hitchhiking Problem

We consider an instance of a dynamic hitchhiking problem as follows:

- **A Road Infrastructure:** represented by a graph $G = \langle V, E \rangle$, roads are modeled by edges $E = \{e_1, e_2, \dots, e_n\}$ and road intersections by nodes $V = \{v_1, v_2, \dots, v_n\}$.
- **A Set of Riders.** R , with a rider $r \in R; r : (id, v_s, v_l, v_e, wt, p)$ defined respectively by a unique identifier, a departure position, a current position, a destination position, a total waiting time and a perception. The waiting time wt corresponds to the current waiting time of the rider in the simulation. The perception p of a rider corresponds to the set of the nodes accessible through candidate drivers. It is initialized with its starting node.
- **A Set of Drivers:** D , with a driver $d \in D; d : (id, v_s, v_l, v_e, trip, c)$ defined respectively by a unique identifier, a departure position, a current position, a destination position, a trip and a capacity. The driver's trip is the set of the nodes that compose the shortest path from its start node to its end node. The capacity of a driver corresponds to the number of seats available in his vehicle.

Such representation of the road infrastructure permits us to compute the shortest path and the distance between two nodes. It also permits us to detect common nodes in the itineraries of system users.

We are using a discrete time and space simulation. Time evolves at constant intervals and traveling from one node to an adjacent node requires a unit of time. Therefore, in our simulation, time and distance are merged and we denote the distance-time between two nodes v_i and v_j : $dt(v_i, v_j) = SPL(v_i, v_j)$, SPL being the shortest path length between the two nodes. Each rider and driver can travel on the graph from node to adjacent node. Several riders and drivers may be present on the same node. At each time step, all riders and drivers present in the system can perform an action based on their behavior.

2.2 Formulations

To identify whether a trip sharing is possible between a rider and a driver, we use several constraints.

The Shareability Constraint: for a driver d_j to be a candidate for a ridesharing with a rider r_i , he must pass through one of the nodes present in the perception $r_i.p$ of this rider.

$$r_i.p \cap d_j.trip \neq \emptyset \quad (1)$$

The Transferability Constraint: for a passenger r_i ridesharing with a driver d_j to transfer with another driver d_k at the transfer node v_{trs} , the first driver d_j must arrive before or at the same time as the second driver d_k at the transfer node v_{trs} .

$$dt(d_j.v_l, v_{trs}) \leq dt(d_k.v_l, v_{trs}) \quad (2)$$

$$dt(d_k.v_l, v_{trs}) - dt(d_j.v_l, v_{trs}) \geq 0 \quad (3)$$

If the ridesharing is possible, the left-hand side result of the Eq.3 is called the delay :

$$\text{delay}(d_j, d_k, v_{trs}) = dt(d_k.v_l, v_{trs}) - dt(d_j.v_l, v_{trs}) \quad (4)$$

The Delay. then represents the waiting time of the rider on the transfer node between the arrival of the first driver and the departure of the second driver. Concerning the delay of a driver d_j to pick up a passenger r_i not being in a car - and thus in a stationary state - it corresponds to the time distance between the current node of the driver $d_j.v_l$ and the current node of the passenger $r_i.v_l$.

$$\text{delay}(r_i, d_j, r_i.v_l) = dt(d_j.v_l, r_i.v_l) - dt(r_i.v_l, r_i.v_l) \quad (5)$$

$$\text{delay}(r_i, d_j, r_i.v_l) = dt(d_j.v_l, r_i.v_l) \quad (6)$$

We have shown how to establish candidate ridesharing drivers. It is now a question of establishing whether a candidate driver profits to a rider's trip. Indeed, one can imagine that a driver who is heading towards the opposite direction, although satisfying the stated constraints, is not necessarily relevant. To evaluate the profit of ridesharing with a driver, we use two values: the contribution and the delay.

The Contribution of a Move to a node $v_k \in d_j.trip$ to a rider's journey is described as the difference between the shortest path length (SPL) between the rider's current node $r_i.v_l$ and its arrival node $r_i.v_e$ and the shortest path length between the target node v_j and the same arrival node $r_i.v_l$.

$$\text{contrib}(r_i.v_l, r_i.v_e, v_k) = \text{SPL}(r_i.v_l, r_i.v_e) - \text{SPL}(v_k, r_i.v_e) \quad (7)$$

We consider relevant a path sharing between a rider r_i and driver d_j to a node v_k if the delay does not exceed the contribution.

$$\text{contrib}(r_i.v_l, r_i.v_e, v_k) > \text{delay}(r_i, d_j, v_k) \quad (8)$$

$$\text{contrib}(r_i.v_l, r_i.v_e, v_k) - \text{delay}(r_i, d_j, v_k) > 0 \quad (9)$$

The Profit of a Ridesharing: the result of the left-hand side of Eq.9 performing the difference of the driver's delay over the contribution of the move to a node in the driver's path results in the profit.

$$\text{profit}(r_i, d_j, v_k) = \text{contrib}(r_i.v_l, r_i.v_e, v_k) - \text{delay}(r_i, d_j, v_k) \quad (10)$$

Thus, a negative or zero profit is of little interest, while a positive profit allows the hitchhiker to progress efficiently towards his destination. However,

a driver with a null or negative profit can lead a rider to another driver who is much more interesting. It is therefore necessary to be able to not only evaluate the direct contribution of a driver but also the opportunities that he offers with his itinerary.

Therefore, we define the objective function of a rider as maximizing the sum of the drivers' profits.

$$\max \sum_{j=0}^{\text{size}(D)} \sum_{k=0}^{\text{size}(d_j.trip)} \text{profit}(r_i, d_j, v_k) \quad (11)$$

3 THE SUGGESTED MULTI AGENT ARCHITECTURE

In this section, we detail our approach based on an individual-centered simulation and a transfer graph.

The drivers and riders present in our hitchhiking system are autonomous and interactive. They make their proper decisions and communicate to share information about their journey. A multi-agent system (MAS) permits the organization of such a population: it is composed of autonomous agents who have their own behavior and characteristics and who interact with their environment. In a MAS, the agents are not systematically individuals on the move, they may also be responsible for system-related tasks such as collecting and sharing information on the user agents.

Our multi-agent system is composed of various agents with specific functions and purposes. Driver agents D aim to arrive at their destination as quickly as possible and without detours. Rider agents R want to reach their destination by ridesharing with driver agents. In order to do so, they have to decide at each step of the simulation what action to perform in order to get closer to their goal.

In this article we detail two rider agent behaviors. The first behavior is the naive hitchhiker, it reproduces the behavior of a real hitchhiker. A hitchhiker usually takes the first vehicle permitting him to progress on its journey, it is not connected and does not plan its transport. According to this idea, a naive rider agent only consider its current node, it does not browse the rest of the environment. If one or more drivers appear on its current node, it evaluates the contribution of their next move. If it turns out that the next movement of one of the drivers makes him move towards its goal, then it gets into the vehicle, otherwise it does not move and increment its waiting time.

The second behavior is called the ReTAG hitchhiker (Real-time Trip Availability Graph). It corresponds to a hitchhiker connected to a transport service allowing him to have information on the drivers in the environment. He can then plan a dynamic and

optimized route. If one or more drivers appear on its current node, the rider evaluates their profit as well as the profit of the drivers accessible on the way via a transfer. Moreover, it takes into account the drivers passing through its current node in the future. Indeed, it may be better to wait a few simulation steps for another driver providing a better solution.

The need for this rider behavior to have limited information about the environment leads us to detail the *tsa* transport service agent. This agent acts like a blackboard. It stores the current and future positions of the drivers and associates to them the related time delay, i.e. the number of simulation steps needed before reaching the concerned position. Thus, when a new driver agent appears in the system, it transmits its route to the *tsa* agent. The *tsa* agent updates at each simulation step the blackboard by decrementing the delays and by removing or adding drivers on each node in a dynamic way. To establish its perception and in order to make a decision, a ReTAG passenger agent sends a query on its current perception, i.e the set of nodes accessible via candidate drivers, to the *tsa* agent, which return the set of admissible driver agents, their trips and their delays. The rider agent applies the ReTAG approach, whose algorithms are detailed later in this paper, and updates its transfer graph and perception. It will do this again as long as new candidate drivers are returned as a result of the query on its perception to the *tsa* agent. Finally, it applies the objective function detailed in the section 2.2 and identifies whether it should update its position following the optimal driver's move or remain in the same place and increment its waiting time. The identification of this set of nodes and associated drivers is schematically shown in Fig. 1.

4 THE REAL-TIME TRIP AVAILABILITY GRAPH APPROACH (ReTAG)

Once the set of admissible driver agents is returned by the *tsa* transport service agent, the ReTAG rider agent builds the ReTAG graph.

4.1 Definition of the ReTAG Graph

The ReTAG graph must contain enough information to allow the rider agent to identify the optimal solution at each simulation step, but must also be light enough to be browsed and updated regularly and an inexpensive way. It is therefore excluded to create a graph including all the nodes from the response

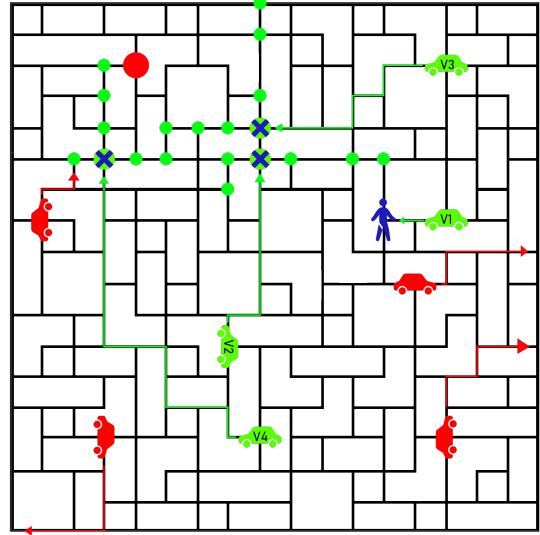


Figure 1: Diagram of the process of identifying the set of reachable positions (green nodes) via compatible drivers (green cars) to the situation of a rider (blue man). The possible transfers are represented by the green nodes with a blue cross and the arrival node is in red. The discarded drivers (red cars) violate the constraints. There exists a path between the current position of the rider and his arrival.

to the query. We therefore define the ReTAG graph $G_{rtg} = \langle V_{rtg}, E_{rtg} \rangle$ overcoming this issue.

We define two types of nodes in this graph. The first type is the transfer node, which is added to the graph in the case of a possible transfer between several drivers and if the travel opportunities associated with this transfer result in a positive profit. The second type is the profitable node. When a rider agent is looking for the best route to his destination, there may not yet be a ridesharing sequence that would allow him to fulfill his objective. In this case, his goal is to take the path that gets him as close as possible to his destination. It is then necessary to limit the interest of a ridesharing to the position limiting the profit, this limit is represented by the profitable node. Each of the above mentioned nodes has an attribute: the arrival time $arrTime$ representing the number of simulation steps needed by a rider to reach the concerned node. It is made of the sum between the previous and current delays of the drivers and the previous and current distances between each node of the graph. We finally note that since the set of nodes of the ReTAG graph are above all nodes of the route graph, this set is a subset of the nodes of the route graph $V_{rtg} \subseteq V$.

The edges of the ReTAG graph contain information about the trip between two nodes. These edges are oriented according to the direction of the driver agent responsible for the trip. They contain the identifier of the driver agent, the contribution of the trip

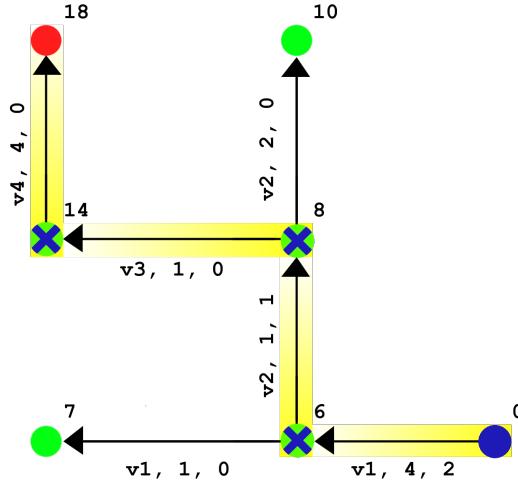


Figure 2: Example of a ReTAG graph built from the scenario in Fig.1. The blue node and the red node are respectively the departure and arrival node of the rider agent. The green nodes and green nodes with a blue cross are respectively profitable nodes and transfer nodes. The different arcs represent the possible trips between the nodes. The information contained on the arcs are respectively the identifier of the driver responsible for the trip, the trip contribution and the delay (see 2.2). The best path (at this step of the simulation) to the arrival node is highlighted in yellow.

and the delay, i.e. the waiting time before being picked up. It is important to mention that this model is generic and that we could add other attributes to these edges. An example of the information contained in these edges is shown in Fig.2.

4.2 Generation of the ReTAG Graph

A ReTAG graph is built recursively by connecting, step by step, the subgraphs resulting from the exploration of the space drivers' trip. For each new driver compatible with the situation of the rider (at the departure node or by a transfer and respecting the constraints), a sub-graph of exploration of the trip of this driver is created. The objective is to recursively identify if a profitable path exists in the solution space. Thus, during the recursion, if a node is identified as profitable, the subgraph resulting from the exploration is connected to the rest of the ReTAG graph and so on until the set of possible solutions is covered. We note that with this method, each driver agent or node of the road graph G is visited and studied only once.

The generation of the ReTAG graph is based on two algorithms. The algorithm 1 is named ICRG for Initialization and Connection algorithm of the ReTAG Graph. It aims at initializing the ReTAG graph with the drivers passing through the starting node of the rider (ICRG, L1-2). It runs the algorithm 2 on each

of these candidate drivers and connects the subgraphs resulting from the exploration of the possible transfers in their trip if a profitable solution is found (ICRG, L3-8). The ICRG algorithm returns the ReTAG graph at the end of the process (ICRG, L9).

Algorithm 1: ICRG: Initialization and Connection algorithm of the ReTAG Graph.

```

Input:  $G$  = road infrastructure graph,  $r$  = a rider
Output:  $G_{rtg}$  = the rider ReTAG graph
1: instantiate  $G_{rtg}$  with rider current node ( $r.v_l$ ,  $arrTime = 0$ )
2:  $AD$  = query  $tSa$  for available drivers passing by rider current node  $r.v_l$ 
3: for all  $d \in AD$  do
4:    $node = REDT(d, r.v_l, delay(r, d, r.v_l))$ 
5:   if  $node$  not None then
6:      $G_{rtg}.addEdge(r.v_l, node.d.id, contrib(r.v_l, r.v_e, node), delay(r, d, r.v_l))$ 
7:   end if
8: end for
9: return  $G_{rtg}$ 

```

The algorithm 2 is referred as REDT for Recursive Exploration of Drivers' Trips algorithm. This algorithm is responsible for recursively exploring drivers' trips in search of profitable or transfer nodes. It considers as parameters a driver candidate to ridesharing $curD$, the node studied in the previous recursion $prevNode$ and the time accumulated during the previous recursion $prevArrTime$ (rider travel time and rider waiting time). These variables are essential to check if the ridesharing constraints are not violated and to maintain the time consistency in each exploration. Thus, $prevNode$ allows to limit the set of nodes to consider in the driver's trip $curD$. Indeed, all the nodes prior to $prevNode$ will represent the past itinerary of the driver at the time of ridesharing. The subset $curD.subTrip$ is then created and includes all the nodes of the driver's trip from $prevNode$ excluded (REDT, L1). The variable $prevArrTime$ initializes the time reference in the recursion (REDT, L2).

We then initialize two variables: $firstNode$ and $lastNode$ (REDT, L3). These variables are used to find the first and last node added to the subgraph of the profitable and transfer nodes. Indeed, once the path of the current driver $curD$ has been explored, it is necessary to initially determine if a profitable path has been found from this driver. If so, it is necessary to determine which node to connect to the graph of the previous recursion. This function is filled by the variable $firstNode$. It is initialized to *None* so that, if at the end of the recursion there is still no node associated with this variable, then there is no interest in carpooling with this driver (ICRG, L5).

Concerning the $lastNode$, it stores the last node added to the current subgraph during the traversal of the nodes of the current driver $curD$. We are going to

Algorithm 2: REDT: Recursive Exploration algorithm of Drivers' Trips.

Input: $curD$: the current studied driver, $prevNode$ the previous studied node, $prevArrTime$: the time it takes the rider to reach the previous node with $curD$

Output: $firstNode$: the first node of the driver's trip added to the ReTAG graph if any

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1:  $curD.subTrip = curD.trip$  nodes from  $prevNode$  to the end of the trip
2:  $arrTime = prevArrTime$ 
3:  $firstNode = None$ ,  $lastNode = None$ 
4: for all  $node \in curD.subTrip$  do
5:    $arrTime += 1$ 
6:    $AD = \text{query } tsa \text{ for available drivers passing by } node$ 
7:   for all  $d \in AD$  do
8:     if  $\text{delay}(curD, d, node) \geq 0$  then
9:       # possible transfer on  $node$  between  $d$  and  $curD$ 
10:       $newNode = \text{REDT}(d, node, \text{delay}(curD, d, node) + arrTime)$ 
11:      if  $newNode \neq None$  then
12:        # profitable node found through transfers
13:        if  $node \notin G_{rtg}$  then
14:           $G_{rtg}.addNode(node, arrTime)$ 
15:        end if
16:        if  $firstNode == None$  then
17:           $firstNode = node$ 
18:        else
19:           $G_{rtg}.addEdge(lastNode, node, curD.id, contrib(lastNode, r.v_e, node), delay = 0)$ 
20:        end if
21:         $lastNode = node$ 
22:         $G_{rtg}.addEdge(node, newNode, d.id, contrib(node, r.v_e, newNode), delay(\text{curD}, d, node))$ 
23:      end if
24:    end if
25:   end for
26: end for
27: if  $firstNode == None$  then
28:   # no transfer found or no profitable node found through transfers
29:   search for the most profitable node in  $curD.trip$ 
30:   if exists a profitable node then
31:      $firstNode = \text{most profitable node}$ 
32:   end if
33: end if
34: return  $firstNode$ 

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detail its utility by analyzing the algorithm 2. The REDT algorithm traverses each node $node$ of the sub trip of the current driver $curD.subTrip$. The reference time $arrTime$ is then incremented by 1: a movement from one node to another adjacent node requiring 1 simulation step. The passenger agent makes a query to the transport service agent tsa on $node$ to obtain the drivers passing through this node. The result of this query, namely the set of available drivers, is stored in a new set AD (REDT, L4-6). For each of these drivers, we check if the transferability constraint defined in section 2.2 is respected. If so, a transfer is possible and the algorithm performs a new recursion on the driver d and the node $node$ (REDT, L7-9). If this new recursion returns a node, it is the first node of the subgraph of this new recursion. We thus obtain

the information that the driver currently studied $curD$ allows the rider to reach a profitable node by means of a transfer on the node $node$. The node $node$ is then a node of interest and is added to the subgraph of the current recursion (REDT, L11-15).

Finally comes the linking phase between the subgraph resulting from the transfer with the driver d and the subgraph of the current driver $curD$. First, the transfer node $node$ is added in the ReTAG graph. If it is the first node added in the graph for the current driver $curD$, we associate its value to $firstNode$. Otherwise it must be linked with an edge to the last node added during the current recursion. This node is not necessarily the node preceding $node$ in the subpath of the current driver. Indeed, we have previously specified that only profitable or transfer nodes are included in the ReTAG graph. Some nodes of the driver's trip are omitted because they are not of interest to the rider. It is therefore essential to have a variable such as $lastNode$ and to update it each time a node is added (REDT, L16-21). Finally, the algorithm links by an edge the subgraph resulting from the transfer with the driver d with the subgraph of the current driver $curD$ on the transfer node $node$ (REDT, L22).

It may happen that after having visited all the nodes of the trip of the current driver $curD$, the algorithm has not identified any interesting transfer for the passenger. In this case, the algorithm looks for the most profitable node of the driver and associates it with the $firstNode$ (REDT, L27-33). If no such node exists, the driver and his path are naturally discarded by both algorithms (ICRG, L5 and REDT, L11).

Once a rider agent has generated its ReTAG graph, it searches for the path maximizing its profit by applying the objective function described in section 2.2. The resolution is simplified because the rider only has to find the path, i.e. the edge sequence, in the ReTAG graph maximizing the sum of the differences of the delay over the contribution.

5 EXPERIMENTS

This section details the framework of our simulation and the results derived from it. We define the different parameters used in the hitchhiking problem instance and compare the naive hitchhiker with the hitchhiker using the ReTAG approach.

5.1 Experimental Setup

Each of the two rider behaviors (naive and ReTAG) is tested on 50 different instances and the resulting data are averaged. An instance is composed of a route

graph, a set of driver agents and a set of rider agents. For the generation of our route graph, we chose to study a grid graph because many works use the city of Manhattan for their experiments as (Alonso-Mora et al., 2017) or (Tafreshian and Masoud, 2020). The streets of this city are organized in a regular grid form with some perturbations like parks for example. Thus, after having generated our road graph in grid form, we apply a perturbation to it. This perturbation consists in randomly removing edges from the graph while checking that the graph remains connected. The departure and arrival nodes of the driver and rider agents are randomly drawn.

We propose a simulation with a continuous generation of drivers while all the riders are generated at the initialization of the instance and their number is fixed beforehand.

5.2 A Simulation with a Continuous Generation of Drivers

The simulation with a continuous generation of drivers allows us to reproduce a real situation where there is an incoming and outgoing flow of drivers in the system. By varying the density of this flow we can simulate a whole panel of road traffic and evaluate the behaviors in situations of scarcity or abundance of the ridesharing offer. The instance resolution ends when all the rider agents have reached their destination.

In this simulation, we generate a road graph of 100 nodes perturbed on 30% of the edges to obtain a convincing road graph. The number of rider agents generated is 100 and the density of the driver flow varies between 25 and 225 in order to generate situations of scarcity and abundance of ridesharing solutions for the riders. In other words, during a simulation step there cannot be more drivers than the defined flow density. Each time a driver agent arrives at its destination and dies, a new driver agent is generated.

The results of this simulation are presented in Fig.3, Fig.4 and Fig.5. In these figures, the variation of the maximum number of drivers present in the simulation for one simulation step, i.e. the maximum flow, is represented on the x-axis. The different metrics studied, such as the average waiting time, the average travel time and the number of simulation steps are shown on the y-axis. Finally, the curves and areas represent respectively the average values and the standard deviation of the data resulting from the application of the ReTAG (orange) and naive (blue) rider behavior. These results show the efficiency of the ReTAG passenger behavior compared to the naive passenger behavior. Indeed, the average number of simulation steps required for all the rider agents to

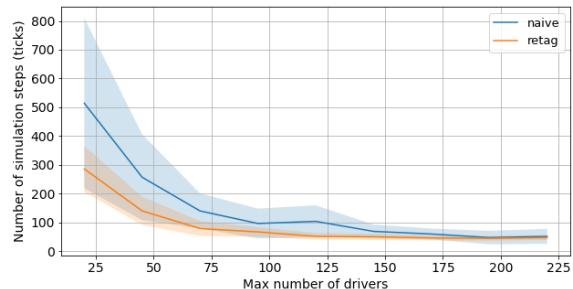


Figure 3: Number of simulation steps required to achieve an instance according to the maximum number of drivers and the rider behaviors: naive in blue, ReTAG in orange. The lower the values, the better the result, as the target is to minimize the number of steps.

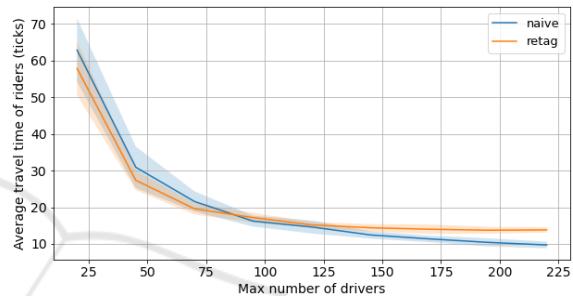


Figure 4: Average travel time of rider agents according to the maximum number of drivers and the rider behaviors: naive in blue, ReTAG in orange.

arrive at their destination is reduced considerably as shown in Fig.3. This reduction is more pronounced when the flow of drivers is in a situation of scarcity, i.e. for a maximum flow of drivers between 25 and 75 approximately. It is also in this interval that we observe a shorter travel time for ReTAG riders than for naive riders in the Fig.5. Once a maximum driver flow of 150 is reached, the ReTAG passenger's curve stabilizes while the naive passenger's curve continues to decrease and consequently does better in terms of travel time. This phenomenon can be explained by the fact that a rider with ReTAG behavior does not only consider the contribution of a ridesharing but also the

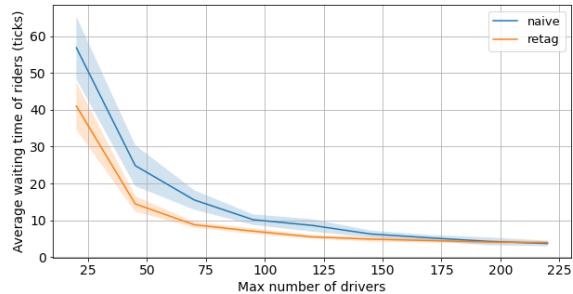


Figure 5: Average waiting time of riders according to the maximum number of drivers and the rider behaviors: naive in blue, ReTAG in orange.

waiting time associated to each transfer. He therefore favors motion over waiting, i.e., he prefers to make detours that lengthen his trip than to stay in one place and wait. This phenomenon is emerging and very interesting because once a situation of solution abundance is reached, ReTAG riders balance their travel time against their waiting time, i.e. the components of profit. The Fig.5 tends to confirm this justification with an average waiting time of ReTAG passengers lower than that of naive passengers regardless of the maximum flow of drivers.

6 CONCLUSION

In this paper, we present a recursive algorithm named ReTAG for solving and optimizing the hitchhiking problem. We define the characteristics of this problem and propose an individual-centered simulation using a multi-agent architecture to study it. A comparative study of two rider agent behaviors is performed on more or less complex problem instances. The first one simulating the behavior of a real hitchhiker, namely the naive hitchhiker, and the second one simulating a hitchhiker connected to an information system, namely the ReTAG hitchhicker. The results of this study imply better performance for the ReTAG hitchhiker and this in particular when the situation is complex.

This study was designed as a framework for addressing the hitchhiking problem, which has been only slightly studied in the past. It would therefore be interesting to go deeper into the model by overcoming the abstraction of time and space. Each edge would then have a distance and a speed limit allowing to calculate a realistic travel time for each trip. On the other hand, the comparison with the slugging problem (Ma and Wolfson, 2013), i.e. hitchhiking with meeting places, can be very interesting to estimate the impact of the concentration of demand and supply as a means of connection.

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