Simulation of Autonomous Transit On Demand for Fleet Size and Deployment Strategy Optimization

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Abstract

Autonomous transit on demand (ATOD) is a potential future public transit mode, which appeals to a lot of researchers and policymakers. In the project, ATOD is simulated in MATSim to explore the optimal fleet size and deployment strategy to help policymakers decide how to introduce the new transport system in the future. The simulation enables the system to explore the optimization automatically under specific constraints with the MATSim evolutionary algorithm.

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1. Introduction

Public transit is a significant transport mode worldwide but still faces some challenges. On one hand, from passenger’s perspective, issues such as detouring, the uncertainty of waiting time and frequent transfers make public transit inconvenient or unattractive. On the other hand, from operator’s perspective, low occupancy may lead to economic loss. With the development of autonomous vehicles (AVs), public transit may step into a new era. Some researchers treated AVs together with the shared economy as a promising alternative to conventional taxi service and simulated AVs as shared autonomous vehicles (SAVs) with agent-based modeling, a dynamic door-to-door ride-sharing service. Several simulations of SAV were done recently in Austin\textsuperscript{1}, Berlin\textsuperscript{2} and Zurich\textsuperscript{3} among others. Some researchers studied the potential of personal rapid transit (PRT), which offers stop-to-stop service on demand. For example, Chebbi\textsuperscript{4} simulated PRT with agent-based modeling. In this paper, the autonomous transit on demand (ATOD) system consists of stop-to-stop shared rides in minibuses following dynamic routes and responding to requests.

For policymakers and operators, optimal fleet size and deployment strategies are the main concerns. Fagnant\textsuperscript{1} simulated SAV with varying fleet size and define optimal fleet size from the economic perspective. Brownell\textsuperscript{5} calculated the greatest number of vehicles among 48 30-min segments as optimal fleet size with pixelated transit grid. Spieser\textsuperscript{6} assessed the optimal fleet size, taking the cost of vehicles, customer walk aways and the expense of moving empty vehicles stop-to-stop service on demand. For example, Chebbi\textsuperscript{4} assessed the potential of personal rapid transit (PRT), which offers stop-to-stop service on demand. For example, Chebbi.
vehicles into account. Li\textsuperscript{7} calculated optimal fleet size with cost-effectiveness analysis. However, few researchers consider the influence of fleet size and deployment strategies on vehicle occupancy, which is one of the remarkable characteristics of public transit. The paper explores the optimal fleet size and deployment strategies of ATOD, considering the benefit of ride-sharing. The purpose is to help operators, authorities and planners decide the appropriate fleet size and deployment strategies of ATOD to satisfy the demand with high-occupancy vehicles.

The code of the project is available in github: https://github.com/strawrange/MasterThesis

2. Methodology

The simulation is based on existing DRT (Demand Responsive Transit)\textsuperscript{8} module of the Multi-agent Travel simulator (MATSim)\textsuperscript{9}. In this module, ATOD with dedicated stops, centralized dispatching algorithm, and dynamic ride-sharing has already been successfully implemented. As shown in Fig. 1, in DRT module, a typical user goes first to the closest transit stops, submits a travel request upon arrival and waits for a minibus. Among all the available minibuses, the request will be dispatched to the one with least time loss, taking both pick-up time loss and drop-off time loss into account. Giving priority to the accepted passengers, the system will reject the request once specific accepting constraints are not satisfied.

In most simulations, the initial fleet size and location is pre-defined, but some researchers use simulation to find an optimal fleet size. Fagnant\textsuperscript{10} runs a seed simulation to define an appropriate fleet size, which generates vehicles once the passenger waits for more than 10 minutes. This approach can guarantee the passengers’ waiting time, however, as there is no penalty for extra vehicles with low-occupancy in the model, the fleet size is overestimated. Therefore, as shown in Fig. 1, the following functionalities are incorporated into the DRT module:

- On demand vehicles deployment
• Mode choice: Order a new minibus vs. Request a ride
• Popular vehicle incentive
• Cost-based routing module

The main objective of these functionalities is to create a trade-off between calling a new minibus, and requesting a ride in one of the deployed vehicles. If an agent calls a new minibus, it won’t have to wait in the transit stop, it won’t be aborted of the simulation but that vehicle must be popular for other agents or indispensable. If an agent tries to travel in one of the moving minibuses, it will have to wait, it can be aborted if its request is rejected many times, but it won’t be penalized for calling a new vehicle. These agents can also decide to walk longer at the beginning or the end of their trips to find an appropriate vehicle.

Driven by the evolutionary algorithm, the simulation will try to reach an equilibrium with least aborting, least vehicles and most ride-sharing through iterations. The fleet size and deployment of the equilibrium will be considered as the optimal solution.

2.1. On demand vehicles deployment

On-demand vehicle deployment consists of on-demand vehicles generator and vehicle abandoning algorithm. The generator will create the new vehicle for the passenger who calls a new vehicle at the passenger’s current location. If a vehicle is idle for more than I minutes (I is defined as vehicle idle time in configuration), the vehicle will be marked as rarely-used and removed from the simulation.

2.2. Mode choice: Order a new minibus vs. Request a ride

Agents in MATSim can evolve to equilibrium through changing mode, routing, and time allocation. In order to find the optimal fleet size in the system, agents are allowed to evolve between two modes, new DRT call and DRT request. For agents with the new DRT call mode, minibuses are created whenever they arrive at the stations. Agents with the DRT request mode are not allowed to create any vehicles and they have to wait till the request is accepted by existing minibuses. Every U minutes (U is defined as request update time in configuration), the rejected request will be submitted again. To improve the computational performance, once a DRT requester waits for more than W minutes (W is also defined in configuration as the maximum passenger waiting time), the agent will be labeled as ”stuck and abort” in the system and it will get significant penalization for not finishing its daily plan. In other words, agents who cannot find a deployed minibus are encouraged to call new vehicles; while a new DRT caller whose vehicle is not frequently-used will be penalized. The balanced ratio of new DRT callers and a DRT requester emerges from the evolutionary algorithm of MATSim, and represents the initial location of minibuses and the optimal fleet size.

2.3. Incentive and scoring

In order to find the optimal fleet size, it is important to limit the number of new DRT callers. In MATSim, all plans will be rerouted based on the score of previous iterations. Therefore, ride-sharing can be encouraged through scoring bonus or penalty. In the simulation, popular vehicle incentive is implemented.

Popular vehicle incentive $I_r$ is calculated directly by the total number of passengers traveling with the vehicle.

$$I_r = \beta_r \cdot P + C_r$$  \hspace{1cm} (1)

The constant $C_r$ of each new DRT calling trip is -30 util, $\beta_r$ is 1 util/passenger and P is the number of passengers boarding on the vehicle. In other words, new DRT caller will be awarded if the minibuses he or she creates serve more than 30 passengers. The more popular the vehicle is, the higher score the caller of the vehicle can get.

Apart from the incentive, the maximum walking distance is defined. Walking is highly recommended for the short-distance trip. It is widely acknowledged that half-mile (approx. 800m) is an appropriate and comfortable walking distance. For the purpose of encouraging more DRT as well as allowing short-distance walking, maximum walking distance 800m is introduced.
2.4. Cost-based Routing Module

For traditional public transit mode, passengers always compare different transit stops and choose the most satisfying one in terms of traveling time. In DRT module, passengers always go to the closest stop to call a minibus but it is not real. In the reality, for conventional taxi service, people are eager to walk a little bit more to call a taxi on the main street or to call a taxi on the other side of the road to avoid detours. To simulate these behaviors, new routing module is implemented in the system under the assumption that agents prefer stops with less waiting time and less detouring. The initial waiting time of each stop is zero, and the waiting time of each stop will be updated each iteration with the actual value of the previous iteration. Similar to transit router, the new routing module will compare the total travel time, which is the sum of traveling time of access walk, waiting time, travel time of minibuses and traveling time of egress walk of all stops within 1000m of origin or destination and choose the one with least total travel time. The waiting time is the average waiting time of the passengers who depart within the 15-minute bin from the stop in the last iteration. For example, if one DRT requester is going to depart at 15:09 at iteration 3, the passenger will take for all stops within the 1000m radius of origin as possible origin stops and all stops within the 1000m radius of destination as possible destination stops. For all possible origin and destination stops, the passenger will calculate and compare the sum of the cost of walking to the possible origin stop, average waiting time from 15:00 - 15:15 of origin stops at iteration 2, traveling from origin stops to destination stops, walking from possible destination stop to destination. The agent will choose the origin and destination stop with least cost and compare the least DRT traveling cost with direct walking cost and decide the travel route with the corresponding routing module. As mentioned above, if the walking distance is more than 800m, the walking cost will be infinitely high. It is noted that new DRT caller is routed with the similar routing module but exclude waiting time in the cost calculation. As shown in the Fig. 2, among the six possible DRT routing and one direct walk routing, despite the fact that the travel cost from origin to Stop 1(S1) is higher than to S2, as well as the travel cost from S2 to S4 is the least, the agent will choose the red path, origin - S1 - S5 - Destination, because of the compensation of low estimated waiting cost.

![Fig. 2. Cost-based Routing Module (WC: Waiting Cost, TC: Traveling Cost, Red Line: Least Cost Routing)](image)

3. Scenario

<table>
<thead>
<tr>
<th>Parameters for simulation</th>
<th>Value</th>
<th>Parameters for scoring</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial fleet size</td>
<td>0</td>
<td>Marginal utility of waiting</td>
<td>-6 util/hour</td>
</tr>
<tr>
<td>Vehicle capacity</td>
<td>8 seats</td>
<td>Constant of DRT request</td>
<td>-1 util</td>
</tr>
<tr>
<td>Vehicle idle time</td>
<td>1800 s</td>
<td>Marginal in-vehicle utility of DRT request</td>
<td>-4 util/hour</td>
</tr>
<tr>
<td>Detour tolerance</td>
<td>600 s</td>
<td>Constant of new DRT call</td>
<td>-30 util</td>
</tr>
<tr>
<td>Request update time</td>
<td>600 s</td>
<td>Marginal in-vehicle utility of new DRT call</td>
<td>-4 util/hour</td>
</tr>
<tr>
<td>Maximum passenger waiting time</td>
<td>3600 s</td>
<td>Marginal utility of walk</td>
<td>-5.8 util/hour</td>
</tr>
</tbody>
</table>

The simulation is executed on the scenario of the Sioux Falls (SD, USA), the population was scaled down to 10% of total population (8483 agents) for computational reasons, and the road capacity was scaled down accordingly. (The
A scenario can be found in: https://github.com/matsim-org/matsim/tree/master/examples/scenarios/siouxfalls-2014) All agents executed exactly two legs during a day, home to work or secondary and work or secondary to home. Sioux Falls is a small city with 1810 nodes, 3359 links and 150 transit stops in the transport network. It is chosen to test the new ATOD implementation because it is simple enough for computation but also complete and realistic enough for reasonable results. Table 1 shows the configuration of the simulation, first part presents the important parameters for ATOD simulation, the second part is the scoring parameters.

At the very beginning of the simulation, there is no pre-defined vehicle in the system. Standard 8-seater ATOD will be generated or erased by on-demand vehicles deployment. The aborted condition of vehicles is that idle time exceeds 1800 seconds. With detour tolerance of 600 seconds, no more than 600 seconds delay of all accepted passengers is tolerated in the simulation, in other words, once the new request causes more than 600s extra time, it will not be accepted. DRT requesting passengers will submit the request every 600 seconds till it is accepted. Once a passenger waits for more than 3600 seconds, it will be labeled as ”stuck and abort” in the system.

The marginal utility of in-vehicle traveling, waiting and walking is defined according to Wardman11, where the marginal utility of walking is 1.45 times more than the marginal utility of in-vehicle traveling and the marginal utility of waiting is 1.5 times more. The constant of new DRT call is -30 util, while the constant of DRT request is only -1 util. These scoring parameters are crucial for the trade-off of new DRT call, DRT request and walk modes. Agents may obtain the same score of walking 10 min as waiting 9min and traveling with DRT 1min. Despite the relatively large negative constant, a new DRT caller whose vehicle serves 50 passengers can get a higher score than DRT ride-sharing passengers with least waiting time, even a new DRT caller whose vehicle only serves himself or herself can get a higher score than aborted DRT ride-sharing passengers. Calculating the score of each trade-off option, agents are forced to make the decision for an equilibrium where least and appropriate deployed vehicles can satisfy all the demand in the city.

4. Data Analysis

4.1. Fleet Size

As shown in Fig.3, the two peaks show the temporal distribution of fleet size is in line with the travel demand. During the peak hour, around 240 - 250 vehicles are needed to satisfy the demand while during the off-peak hour, only around 30 vehicles are in use. More than 90% of total trips share rides, and more than 40% of total trips are with high occupancy (more than 6 passengers during the trip). A relatively high proportion of full occupancy can be explained by the limitation of vehicle capacity, which means probably more than 8 passengers are willing to board in one vehicle but some have to wait for the next vehicle. On one hand, as a relatively small city where average in-vehicle time is around 300s, detouring tolerance 600s is far more than enough for a high vehicle occupancy; on another hand, the simulation does not take the comfort factors into account, such as people’s willingness to travel alone, and people’s preference of the fellow travelers. The result shows the minimum number of vehicles may be needed to satisfy the travel demand with high vehicle occupancy.
4.2. Fleet Deployment

Fig. 4 shows the result of on-demand vehicle deployment. The red point indicates the demand, which is calculated by the number of departures, and the black point shows where the vehicles are generated. In both morning and afternoon peak, the spatial distribution of initial vehicle position is close to travel demand. The most popular stop attracts more than 50 new DRT callers ordering their vehicles. During morning peak, some stops in the surroundings are more attractive than stops in the city center; during afternoon peak, some stops in the city center are more popular.

Fig. 4. The spatial distribution of vehicle initial position in morning peak hour (left) and afternoon peak hour (right)

5. Conclusion and Discussion

The paper shows the possibilities of the application of agent-based modeling in areas other than transport simulation. The purpose of the simulation is not only to model the real ATOD system but solve the complex transport optimization problem with the evolutionary algorithm. In the future, more experiments regarding system robustness, sensitivity analysis and computation time should be done for a more realistic and reliable result. Different vehicle capacity, such as 4-seater, 8-seater, and even 20-seater, should be introduced to satisfy different demand. Besides, although Sioux Falls is a completed and realistic scenario, more complicated and huge scenarios, such as Zurich, Singapore, etc., are still needed to be tested for a more meaningful result.

References