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Public transport routing including fixed schedule, shared on-demand and door-to-door services.

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Abstract

Modelling realistic public transport route choices is a key element for transport planning tools. Although these decisions have been modeled based on travel time and travel cost, the emergence of new public means of transport makes the problem more challenging. In this work, we extend the public transport router of a widely used mobility simulation platform called MATSim. Besides fixed scheduled services, the proposed router is able to include on-demand shared services as well as private door-to-door services. With the co-evolutionary algorithm of MATSim, this router records waiting and travel times from previous iterations to improve public transport routes. This allows to take into account interactions between agents when routes are decided. The approach is tested in a model of a future neighborhood of Singapore, where on-demand services complement the existing fixed schedule supply.

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Keywords: Multi-modal routing; Public transport; Mobility on demand; Route choice; MATSim; Agent-based simulation

1. Introduction

Urban mobility is a complex system where decisions and actions of millions of actors are related in time and space. More specifically, in public transport route choice, decisions and actions of a particular user depend not only on their own preferences (value of time, crowd avoidance, willingness to pay) but also on the decisions and actions made by many other public transport users, operators, authorities and even car users, as they can share the same infrastructure.

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Transit assignment is a field widely studied for more than 50 years. The importance of taking into account waiting times in public transport networks was published by Dial[1]. From there, frequency-based models like [2] and [3] where the assignment is not fixed to a run of a fixed service and schedule-based models ([4], [5]) have been advances in the direction of giving alternatives for the route choice dependent on congestion, low-reliable services and crowdedness. Another interest has emerged since the late 1980s ([6], [7]) where hyperpaths (transit routes with more than one option) are assigned to users instead of single paths. Recent works ([8]) propose a dynamic frequency-based assignment with hyperpaths to include effects of queues, congestion and capacity constraints in optimization models.

MATSim[9] is a software framework to simulate transport demand and supply interactions for millions of agents, each representing an individual person. MATSim includes a full simulation of public transport[10], where transit vehicles interact with other vehicles. Each agent has a transport demand represented by a chain of activities to perform in one day at different times in different places. The decisions of how to travel to perform these activities are made before the mobility simulation as a plan. Models to decide the route, start time, mode and/or destination of the journeys per person are included, and they can depend on socio-demographic characteristics. In reality, this decisions can change according to interactions with other travelers. To capture this effect, MATSim executes an evolutionary algorithm to optimize utility of agents. The same day is executed hundreds of times, making changes in some agent planned journeys, and remembering good decisions or forgetting bad decisions. The experience of each agent in relation with others is scored according to utility functions and only good plans are retained. The process reaches a user equilibrium where no agent can improve its score any further without decreasing the score of others in a smaller amount.

2. Public Transport Router

The standard MATSim public transport router was extended to include not only fixed schedule services but also on-demand shared services and door-to-door private services. Furthermore, when routes are chosen, delays in these services are also modeled. To do this, it is necessary to extend the router network and the utility function of its links.

2.1. Network topology and utility functions

The transit router network is the data structure used to model the travel options of public transport users. Paths in this network represent a sequence of travel choices from an origin to a destination.

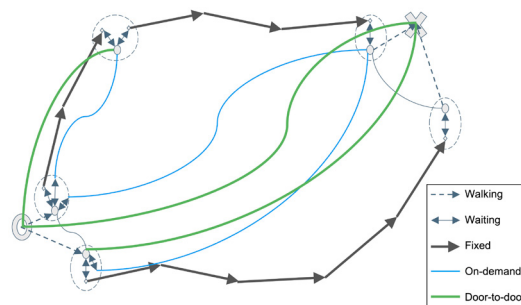


Fig. 1. Router network structure

Table 1. Utility function of each link type of the transit router network

Link type	Utility function
Walking link	$\beta_k * d(l, l)$
Fixed schedule service waiting link	$\beta_w * wt(s, r, t)$
On-demand shared service waiting link	$\beta_w * wt(l, t)$
Door-to-door private service waiting link	$\beta_w * wt(l, t)$
Fixed schedule service travel link	$\beta_m * K_{FS} + \beta_{tFS} * tt(s, s, t) + \beta_m * \beta_{dFS} * d(s, s)$
On-demand shared service travel link	$\beta_m * K_{ODS} + \beta_{tODS} * tt(l, l, t) + \beta_m * \beta_{dODS} * d(l, l)$
Door-to-door private service travel link	$\beta_m * K_{DD2D} + \beta_{tDD2D} * tt(l, l, t) + \beta_m * \beta_{dDD2D} * d(l, l)$

Figure 1 represents a subgraph of the proposed transit router network given an origin on the left and a destination on the right. Different types of links in this network represent different means of transport. Using this network a shortest path algorithm can be applied to calculate the optimal sequence of stages from an origin to a destination. To apply this method, a cost of each link of the network must be modeled. In the MATSim framework, this cost is the disutility of travelling by the mean of transport represented by the link. To include waiting discomfort, waiting links are also included with a corresponding disutility function. Following, the utility function modeled for each link type of the proposed approach is presented.

Where $wt(\dots)$ means waiting time, $tt(\dots)$ travel time and $d(\dots)$ network distance. Besides, FS are parameters and fees for fixed schedule service, ODS for on-demand service, and $D2D$ for door-to-door service. K is a constant fee, β_t is a time-based fee and β_d is a distance-based fee. Finally β_k is the marginal utility of walking, β_w is the marginal utility of waiting and β_m is the marginal utility of money. Other values will be explained in the next sections.

2.2. New data structures for travel times and waiting times

To record experienced travel times and waiting times, new data structures and calculators were implemented. With this, agents can use information from a previous iteration of the mobility simulation to choose optimal public transport routes. This information is saved every 15 minutes and it is plugged directly to utility functions of corresponding links from the transit router network. Thus, for example, agents know if people at a certain public transport stop and at a certain time have to wait a lot for a service, or if walking longer to a less crowded link to order a D2D service is better.

2.2.1. Stop-stop travel times $[tt(s, s, t)]$

For each consecutive stop-stop pair from all scheduled public transport routes, the average travel time is recorded from all vehicles traveling during 15 minutes intervals. This is a proxy of how congested are the roads between two stops. These values are plugged to the utility function of travel links for Fixed Schedule services.

2.2.2. Stop-route waiting times $[wt(s, r, t)]$

For each stop-route combination in the public transport schedule, the times lapsed since passengers arrive to the stop till they enter to a vehicle of the planned route is averaged during 15 minutes intervals. This information is useful for the agents to know how frequent are certain routes and how congested are roads to reach a certain stop. These values are plugged to the utility function of waiting links for Fixed Schedule services.

2.2.3. Link-link travel times $[tt(l, l, t)]$

Similarly to the Stop-stop travel times, average travel times of all vehicles travelling from an origin to a destination road link are recorded. As many link-2-link combinations are never travelled, this structure is convenient for popular trips (e.g. the trip between a train station and a popular shopping mall). These values are plugged to the utility function of travel links for on-demand shared service and door-to-door service.

2.2.4. Link waiting times $[wt(l, t)]$

Average waiting times are recorded for each road link. In the same way than Link-link travel times, many road links are never used to wait for a public transport vehicle, and then, this structure is only useful for popular links, where actually recorded values are meaningful. These values are plugged to the utility function of waiting links for on-demand shared service and door-to-door service.

3. Scenario definition

To test this approach we developed a simulation model of a future neighborhood in Singapore. In the Future Cities Laboratory from the Singapore ETH Centre, a multidisciplinary team lead by Tanvi Maheshwari developed a realistic urban design for this undeveloped region as shown in Figure 2(a). It is assumed that private vehicles can not be used for trips starting or ending inside this area. Thus, agents living, working or performing activities within the neighborhood are forced to use public transport or walk. Other personal mobility devices such as bicycles can be included in the model as fast transit walks if the interaction with other vehicles is negligible.

Four means of transport are offered to travelers, two with fixed schedules (rail and bus), stop-based on-demand shared service (ODS), and door-to-door private service (D2D). Figure 2(b) shows the distribution of stops for fixed schedule services in black and ODS in light blue. The rail line can be seen on the top of the figure and dark blue lines represent bus routes. Trains run with a period of 4 minutes and buses with a period of 5 minutes during peak hours and 10 minutes during non-peak hours. For ODS a fleet of 75 4-seaters, 50 10-seaters and 25 20-seaters is provided while D2D travelers can use 100 vehicles.

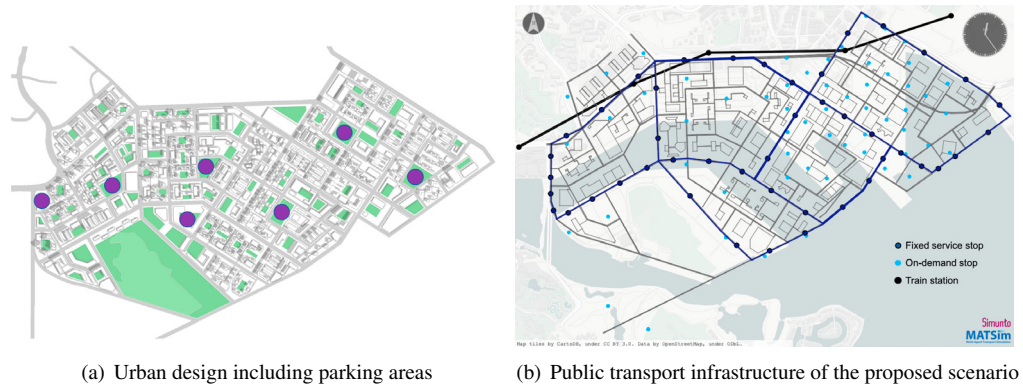


Fig. 2. Simulation scenario (4.5km x 2.8km)

Trips generation and attraction were calculated using time profiles, density, and type of designed buildings in the area. Buildings were characterized according to the size of residential, commercial and other areas. For border effects and background traffic, trips coming from 15 road exits and 2 MRT stops were also included. A total of 537k trips were modeled, including 276k background trips and 261k local trips.

Three simulation scenarios were proposed to evaluate the functionality of the router within the MATSim evolutionary algorithm. The idea is to run simulations with different utility functions and measure the effect of these changes. Some fixed parameters are the marginal utility of waiting time: -6.9 utils/hr, the marginal utility of walking time: -3.0 utils/hr, the marginal utility of walking distance -1.0 utils/km, and the marginal utility of money: 1.0 utils/SGD. Table 2 presents the variable parameters. For the High ODS service scenario the marginal utility of time, the initial monetary rate and monetary rate of distance are increased for the ODS service. In the same manner, these same parameters are reduced for the D2D service in the third scenario.

4. Results

The three scenarios explained above were simulated 40 times using MATSim to reach user equilibrium. The transport demand (agents plans) and transport supply (network, public transport services and on-demand fleets) remained constant in the three scenarios, but agents were allowed to re-route using different utility parameters. The simulated time was 24 hours and the average computation time was 1:25 minutes per iteration using 45 GB of RAM memory and 15 cores. The simulation included public transport and dynamic routing.

Figure 3(a) shows a comparison between the distributions of total travel time of all agents. Comparing with the base case, it can be seen that travel times decrease when the price of the ODS services is increased but also when the price of the D2D decreases. In the first comparison, agents have less incentive to use not fixed shared services and less detouring and less waiting times produce shorter trips. In the second, the difference in total travel time can be explained because D2D trips are faster than shared services, and these services are easier to use.

For more exploration, figure 3(b) presents the comparison of waiting times and figure 3(c) the comparison of walking times between the three scenarios. When the price of ODS services increases, waiting times decrease because fixed services are more used. However, walking times are longer because fixed bus stops are less dense spatially (see figure 2(b)). On the other hand, a lower price in D2D services makes this service more attractive, but as the fleet remains with the same size, the transport supply is not enough and longer waiting times are experienced. This is complemented with shorter walking times because pick-up drop-off facilities are less used.

Table 2. Utility parameters for the three proposed scenarios

Parameter/Scenario	Base case	High ODS	Low D2D
Fixed schedule service marginal utility of time (utils/hr)	-1.0	-1.0	-1.0
On-demand shared service marginal utility of time (utils/hr)	-1.0	-2.0	-1.0
Door-2-door private service marginal utility of time (utils/hr)	-2.0	-2.0	-1.0
Fixed schedule service initial monetary rate (SGD)	-1.0	-1.0	-1.0
On-demand shared service initial monetary rate (SGD)	-1.0	-2.0	-1.0
Door-2-door private service initial monetary rate (SGD)	-1.5	-1.5	-1.0
Fixed schedule service monetary rate of distance (SGD/km)	-0.03	-0.03	-0.03
On-demand shared service monetary rate of distance (SGD/km)	-0.02	-0.05	-0.02
Door-2-door private service monetary rate of distance (SGD/km)	-0.25	-0.25	-0.15

Although the total number of local trips remains the same for each scenario (261k), the number of stages is variable after each evolutionary algorithm. The total number of stages for the Base scenario was 523k, for the High ODS one was 521k and for the Low D2D the total goes down to 491k stages. From there, table 3 presents the share of this number by means of transport. With almost the same stages by D2D service and walk, the difference between the Base and the High ODS scenarios is a change of 20k stages between Fixed service and ODS service. When the price of the ODS service increases, agents basically move to Fixed services sacrificing walking time, as mentioned above. A similar analysis can be done between the Base scenario and the Low D2D scenario. When the price of D2D service goes down, the total number of stages also goes down. Although three times more of D2D service stages are chosen, this drastically reduces the number of walking and ODS service stages.

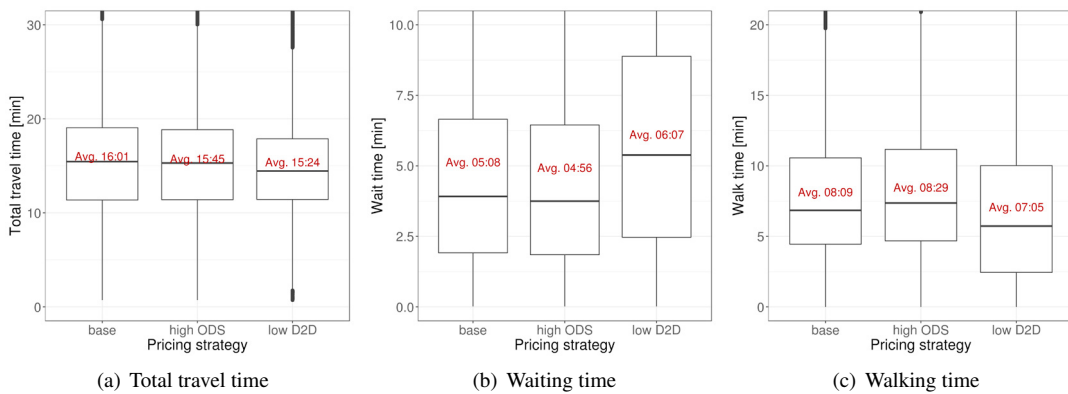


Fig. 3. Travel time, waiting time and walking time distribution comparison of the three scenarios.

Finally, we use figure 4 to analyze the vehicle utilization of the D2D and ODS services in the different scenarios and for different vehicle sizes. The values presented represent the percentage of occupancy of the vehicles during 24 hours. For example, if a 4-seater vehicle has 1 passenger half of the time and it is empty the other half, the average utilization would be 12.5%. The vehicle utilization of D2D services is represented by 1-seater vehicles, while ODS services by 4-seaters, 10-seaters and 20-seaters.

Table 3. Number of stages by means of transport for the three scenarios

Mean of transport/Scenario	Base case	High ODS	Low D2D
Total number of local stages	523k	521k	491k
Number of stages by Fixed schedule service	169k	189k	165k
Number of stages by On-Demand shared service	61k	41k	49k
Number of stages by Door-to-door private service	5k	6k	18k
Number of access, egress or transfer walk stages	288k	286k	259k

As expected, 1-seaters are much more used in the low D2D price scenario, and shared vehicles are more used in the base scenario. Within ODS services, 4-seaters are more utilized than 10-seaters and much more than 20-seaters.

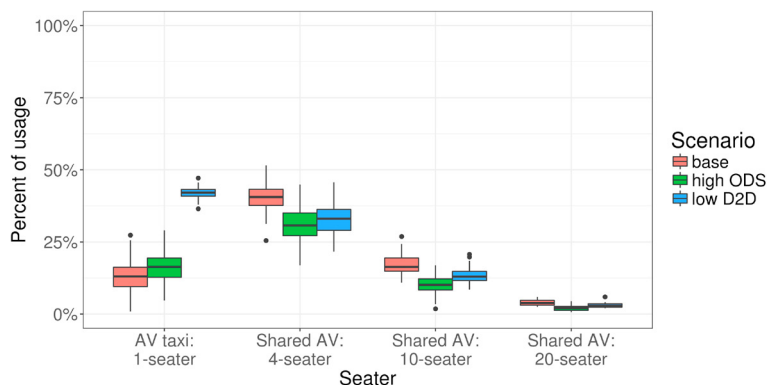


Fig. 4. Vehicle utilization comparison of the three scenarios by vehicle size.

Utility parameters for these three vehicle types are the same, but 4-seaters are more agile because de-tour restrictions and planned travel times are easier to fulfill when fewer passengers are already traveling. It is also shown that shared mobility shared vehicles are less utilized in the two alternative scenarios, although the reason is different.

5. Conclusions and discussion

Shared mobility is one of the best solutions to address the expected increase in transport demand problem in the coming years, hence, it is necessary to understand and forecast how people chose within a collection of public transport alternatives. Even for one trip, users will be able to use fixed services, on-demand shared services or door-to-door services (multi-modal routing). In this work, we developed an extension of the public transport router of an established multi-agent simulation platform, MATSim. With this new feature, agents are able to optimize their travel experience by combining multiple services in one trip. With our initial experiments, we obtained results that show how analysis indicators such as travel times, waiting times and vehicle utilization, vary when different utility functions are defined. The method also takes into account the interaction between transit users when they use limited transport supply. With this, transport system planning can be done at a micro level, not only for the optimization of operations, but also for spatial urban design. Although in this work only variations in the price of the service are studied, agent-based simulations allow to include many dimensions simultaneously. Hence, the future plan is to execute and analyze thousands of simulation scenarios with more variations to obtain more reliable results.

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