A framework for agent based simulation of demand responsive transport systems

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1 Introduction

Demand responsive transport (DRT), such as shared mini busses are an established form of public transport. Typically, these services operate in areas where demand is low (rural areas), very specific (airport shuttles), or only for certain user groups, such as persons with disabilities. With advances in communication technologies and possible driverless operations in the future, DRT systems may become an attractive additional mode also in urban and inter-urban transport. One way to assess and evaluate such services are transport simulations.

In this paper, we describe a DRT extension framework for an existing transport simulation, followed by two case studies that demonstrate the extension's versatility.

2 Methodology

In this study, MATSim (=Multi agent transport simulation) was used for simulations. As an open source transport simulation, MATSim provides all the required extension points and allows for large-scale simulations at high computational speed[3]. The software is written in JAVA and its source code can be accessed via Github[1].

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[1] https://github.com/matsim-org/

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2.1 MATSim and its DVRP framework

MATSim combines a multi-modal traffic-flow simulation with a scoring model (where performing an activity scores positively and traveling negatively) for agents as well as co-evolutionary algorithms that can alter daily routines ("plans") of agents. This three-step process is usually applied to some kind of initial synthetic population (e.g. from census data) repeatedly over several iterations until some form of user equilibrium has been reached.

One of MATSim's existing extensions is the DVRP (dynamic vehicle routing problem) contribution[4]. It is based on MATSim's ability to (re-)plan agents dynamically during the day. The extension contains a framework for scheduling vehicles according to tasks. These are handled by Dynamic Agents (i.e. taxi or delivery truck drivers). Depending on their schedule, these agents may pick up or drop off passengers or goods. One typical use case for the extension are taxi operations, which may be combined with different kind of optimizing algorithms[5][6]. The extension is very lightweight in terms of computational requirements, allowing the simulation of fleets of hundred of thousand dynamic agents within reasonable computational time[1].

2.2 The DRT extension

The DVRP and taxi extensions are so far only able to serve a single request per vehicle at a time. For DRT purposes, where several passengers are onboard a vehicle at the same time, this needs to be extended. The DRT framework, which we choose to call taxibus, was hence equipped with:

- Taxibus Tasks which can serve multiple request at a time.
- A taxibus scheduler which schedules pick ups, drop offs and rides according in accordance with the requests and as calculated by a dispatch algorithm.
- An abstract dispatch algorithm providing typical dispatch infrastructure.

The dispatch algorithm, or *optimizer*, can then be implemented by extending the abstract dispatch algorithm in accordance with the actual use case. The basic principle of each optimizer, however, is usually the same: A list of requests, which may be pre-booked or not, need to be handled. The optimizer should then return a dispatch, consisting of a vehicle, the requests it is meant to handle, and the paths it is meant to travel in between pick ups and drop offs. With this approach, a large set of use cases may be implemented with little additional effort. These could include classical dial-a-ride or paratransit approaches as well as shared-taxi algorithms or even parcel deliveries. Figure 1 provides an overview of the extension and its integration into MATSim.

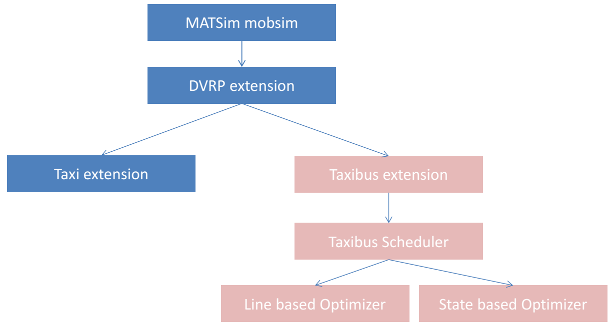

Fig. 1 The implemented DRT extension (red) and its context in MATSim (blue)

3 Case studies

So far, the framework has been combined with two different optimization algorithms. The first one provides a dial-a-ride service to employees commuting between two cities, while the second one puts the focus on optimizing decisions whether to serve or not serve a customer.

3.1 Dial-a-ride services for commuters

Our first case study deals with commuters traveling from their homes in Braunschweig to their work locations in Wolfsburg, Germany. Wolfsburg, a city of 123 000 inhabitants, hosts a large car factory and as such attracts a high share of inbound commuters. Overall, some 75 000 persons are commuting into Wolfsburg[2]. Of these, roughly 10 000 live in Braunschweig. According to a MATSim model of the region ("base case"), 4 000 of these commuters generally traverse home-work-home, before conducting different activities in the afternoon. A majority of these users is traveling by car in the base case, leading to congestion during peak hours both in the simulation and in the real world. Work start time in the morning is generally between 7:00 and 9:00; work end times are more spread out through the afternoon.

In this case study, a dial-a-ride service is introduced for home-work and work-home trips between the two cities. Passengers need to order the service 30 minutes in advance. Busses, with a maximum capacity of 8 passengers, are dispatched from a single central location in Braunschweig (for home-work trips) and from several parking lots in Wolfsburg on the way back. After dropping off customers, busses return to their dispatch point.

When picking up passengers, busses are generally traversing until they are either full or a maximum traversing time (T^{w}_{max}) has passed, before heading out to their destination. There is a maximum number (N_{max}) of vehicles that pick up passengers at the same time. A vehicle is allocated to a passenger, if it is the closest vehicle by beeline-distance. If the number of vehicles traversing is below (N_{max}), an additional vehicle may also be taken into consideration.

In an initial study $T^{w}_{max} = 900s$ and $N_{max} = 8$ is used. This is combined with three different disutilities for using the service: (a) considerably cheaper than public transport; (b) same pricing as for public transport; (c) more expensive than public transport, but cheaper than car usage. The number of available busses was initially not limited, in order to allow the demand to develop and at a later stage determine possible fleet sizes. Due to the distance between both cities and the rather tight time window in the morning, it cannot be expected that many busses will be able to ride for more than one tour in the morning. Simulation runs were conducted for 50 iterations and then compared to the base case. Agents could choose between all three modes freely for 40 iterations and select in between existing plans during the last ten iterations.

Table 3.1 lists the average ride times per commuter in these three cases, as well as in the base case. An introduction of DRT services can help to reduce commuter travel times over all modes (car, taxibus and public transport) by up to five minutes. The (a) pricing would result in 1400 agents using the taxibus. In the afternoon peak, overall travel times would increase in this scenario, meaning that agents are using the service only for the price, rather than travel time savings. Travel times for both car and all users in scenario (b) and (c) are almost the same. This is backed by the fact that many agents are switching from public transport to taxibus in (b), which is less the case in (c). For the scenario (c), a simulation using 50 busses is able to serve the demand, with an average occupation of 6 customers in the morning and 5 in the afternoon.

Overall, the case study shows that DRT services can help to fill gaps where classic public transport fails to attract customers. It may help to reduce congestion, though long term effects should be assessed.

	base case	(a)	(b)	(c)
overall commuters	9763	9763	9763	9763
taxibus users	0	1418	1026	396
est. fleet size	0	130	100	45
all morning	0:56	0:52	0:51	0:51
all evening	0:53	0:55	0:51	0:50
car, morning	0:49	0:43	0:44	0:44
car, evening	0:48	0:43	0:43	0:44

Table 1 Average commuter ride time in hours.

3.2 Dial-a-ride service to a central station

In a second case study, commuters from Braunschweig travel by train to their work. To reach the central station in Braunschweig and take a certain train, persons make a request to be picked up by DRT. This case study focuses on the decision of the DRT to confirm or reject those requests under the uncertainty of future requests. The objective is to confirm as many requests as possible within a certain time horizon. In order to confirm requests that allow many further future confirmations, it is necessary to anticipate possible future requests. A possible approach for stochastic, dynamic problems like the one proposed here is provided by methods of approximate dynamic programming (ADP, [7]). The method used here is approximate value iteration (AVI, [7]), which requires a Markov decision process and offline simulation to evaluate the expected future contribution (value) of being in a certain situation (state) to the overall objective. The parameters for the state description follow [8]. For decisions between possible options, the sum of immediate and future contributions of the options is used. Therefore, two types of simulation are combined here. While the concept of MATSim tries to optimize the agents' travel plans, the acceptance behavior of the DRT dispatcher is the focus of the ADP-part of this case study. The values of states are approximated in an approximation phase in the offline simulation. After this, the knowledge obtained in the approximation phase is evaluated in additional simulation runs where no further approximation of values takes place.

In the specific case study, 100 persons requesting service want to take the same train, while one vehicle with unlimited capacity is available to serve the customer requests. This vehicle starts its tour 1 hour before the arrival time, requests can be made until 15 minutes before the arrival time at the central station. Upon the arrival of a request, the dispatcher decides whether to accept or reject it. The potential customers are uniformly distributed in a service area of $0.83km^2$ in Braunschweig and the request times follow the agents' travel plans. 20 (or 10 or 50)% of the potential customers vary their request time by a maximum of 2 minutes during the first 200 iterations, after this, they still can choose between some possible plans. For the routing, a very basic approach was applied where next customers are only added to the end of the list of accepted customers to be picked up. 1000 iterations were used as approximation phase, 100 as evaluation phase.

As a benchmark, a myopic approach without anticipation was applied that just accepted customers if it was possible to add them to the end of the tour while still arriving to the central station on time. For 20% variation of the request time of the agents, the anticipatory approach yielded a mean of 20.41 accepted customers in the evaluation phase, while a mean of 17.99 customers was accepted for the myopic acceptance policy. For 10 or 50% variation, the myopic approach accepted a mean of 20 and 18.14 requests, while the anticipatory approach accepted a mean of 19.19 and 20.42 requests in the evaluation phase. Only limited conclusions can be drawn from this case study. However, it was possible to implement the dispatcher view into MATSim and for the instances with more stochasticity (20 and 50%), the anticipatory approach was able to confirm more customer requests.

The work on this case study showed that it is a challenging task to implement an algorithm trying to optimize the dispatcher's decisions while the original task of the MATSim environment is to optimize the decisions of the agents traveling in the simulated world. While there seem to be many possible ways to increase the number of persons transported by the DRT, one important change may be an improved routing algorithm. It is also possible to add more features to the problem description. Further, the interdependencies between the solution quality of the dispatcher and the decisions of the transported persons should be further investigated.

4 Discussion

DRT services are a versatile means of transport. In this paper we were able to show, that a common framework for DRT services is a meaningful addition to the current MATSim package. It provides enough infrastructure to easily implement dispatch algorithms depending on the case-study. Further research should hence rather focus on dispatch optimizers, including an improvement to the ones mentioned.

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