Passenger Agent and Paratransit Operator Reaction to Changes of Service Frequency of a Fixed Train Line

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Abstract
Public transport companies should run sustainable transit lines and demand oriented services. This paper presents an enhanced evolutionary model, presented earlier, for the design of demand responsive routes and transport networks. The approach adopts the survival of the fittest principle from competitive developing world paratransit systems with respect to vehicles, market actor characteristics, route patterns and route functions. The model is integrated into a microscopic multi-agent simulation framework, and successfully applied to a naive and a complex scenario. The scenarios include the interaction of paratransit services with conventional public transport. With limited resources paratransit services compete and cooperate with each other to find sustainable routes, which compete or complement existing public transport lines. Besides providing a starting point for paratransit modeling of a region, the approach can also be used to identify areas with insufficient supply of public transport.

Keywords
Multi agent simulation; Demand responsive; Paratransit; Minibus; Jitney; Complex system; Evolutionary algorithm; Public Transport; MATSim

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1 Introduction

The success of a public transport system highly depends on its network design. While transport companies try to optimize a line with respect to running costs, they also have to take care of the demand: The best cost structure will not be sustainable if potential customers leave the system and opt for alternatives, e.g. private cars.

From the operators side a transit line can be optimized by optimizing its headways and stop spacing (Mohring, 1972), its service frequency and bus size (Jansson, 1980) or by adding limited-stop services with high-frequency unscheduled services (Leiva et al., 2010). In addition, optimization should consider the interrelation with other transit lines, i.e. optimization of one single transit line may induce deterioration of quality of another line. Thus, network design and its optimization has been studied. For a summary of network design approaches with focus on bus networks please refer to Ceder and Wilson (1986). Further examples of optimizations focus on meeting the demand of a given OD-matrix (Baaj and Mahmassani, 1995), or on feeder services (Kuah and Perl, 1988; Chang and Schonfeld, 1991) and their interaction with a rail transit line (Chien and Schonfeld, 1998).

More recently, the optimization of feeder transit networks focused on uncertain demand and demand responsive transport systems (DRT), which are related to the dynamic pickup and delivery problem. This includes high-coverage point-to-point transit system with focus on real-time updates of shuttle routes (Cortés, 2003), feeder-corridor systems (Pages et al., 2006) and integrated systems based on a hierarchy of specialized services that complement and coordinate their operations (Fernandez et al., 2008). Regardless of the algorithms used, e.g. genetic algorithms, particle swarm optimization, branch and bound, the systems tend to find a system optimum because the services are cooperating.

Rather than solving one system-wide instance, the present paper will look at a number of competing elements, each of them evolving according to its own optimization procedure. This is related to co-evolution and evolutionary game theory (e.g. Palmer et al., 1994; Arthur, 1994; Hofbauer and Sigmund, 1998; Drossel, 2001). A common topic in such investigations is under which circumstances cooperative structures can emerge despite the competition (e.g. Axelrod, 1984). The structure of the competition will be inspired by paratransit systems. Synthetic transit lines increase or decrease their service frequencies by adding or removing vehicles, depending on each individual line's *fitness*. When no vehicle is left for a line, the line *dies out*.

The structure of this paper is as follows: the next two sections will first give a short introduction to paratransit systems and second define the proposed heuristic approach to solve the transit line route searching problem. The approach is then applied to an illustrative scenario. The paper concludes with an outlook for the approach and possible applications.

2 Paratransit

This section will only give a brief introduction to paratransit systems based on a more comprehensive description of characteristics and underlying principles of paratransit systems published earlier by Neumann and Nagel (2012).

The term paratransit has two meanings when referring to transport. One describes a kind of transport specially fitted to the needs of elderly or physically handicapped people. This paper, however, deals with the second meaning which is public transport ranging from taxis up to bus lines. In most cases, this is a user-demand-oriented mode of transport mainly used in cities of the developing world. Although paratransit shares some underlying principles, it can be distinguished from demand responsive transit (DRT) systems by the way organization takes place. DRT systems heavily rely on a supervising level (controller) which allocates vehicles to individual trips or collective rides (e.g. Cortés, 2003; Pages et al., 2006; Fernandez et al., 2008). Paratransit lacks a supervising control level, but nevertheless is not completely unorganized.

Although one-driver-companies like single car owners exist, the most common type of organization is the cooperative, also known as route association. Cooperatives consist of up to several hundreds of paratransit drivers, and are founded in order to fend off renegades and pirate drivers from the cooperative's service area. Although, in most cases, protection from open competition is the main objective, there may be others, such as the enforcement of minimum standards, facility sharing, or joint negotiation with the administrative or political sector.

A common core distinction among informal services is mentioned by Cervero (2000): whether they are "taxi-like", providing door-to-door connections, or "bus-like", following more or less fixed routes. In general, small-vehicle services, like pedicabs, hired-motorcycles, and microbuses, operate akin to taxis. As passenger loads increase, service providers begin to ply fixed routes because of the impracticalities of delivering lots of unrelated customers to assorted destinations. Accordingly, "bus-like" services consist mainly of larger vehicles like commercial vans, pick-up trucks, and minibuses. Variations may occur in the way that passengers can get on and off along the route or that the driver will make a small detour in order to drop off the passenger. This paper concentrates on minibuses filling the gap between conventional buses and compact vehicles. Such a service – minibuses with fixed routes but without fixed schedule – is often called a "jitney" service. This paper will use the term "minibus service", and refer to the operator as a "paratransit operator" with the understanding that jitney/minibus service is one out of many possible paratransit services.

Most paratransit operators will adapt their route whenever demand changes. This decision is often based on profit maximization by optimizing the income, cutting down expenses, or by optimizing the working time. In contrast to typical transit authority bus drivers, paratransit drivers earn their income from collected fares. In general, there are two models of price structure. The first one is the fixed fare. This can include price steps that decline with distance, e.g. stage fares. The second one relies on fares calculated on a per kilometer basis. In lack of taximeters, the price can be preassigned, e.g. by a cooperative, or can be negotiated with the driver.

The route function is determined by the origins and destinations served. A route can function as a distributor connecting the market to residential areas or as a complementary feeder to mainline routes, e.g. connecting to a metro station. According to Cervero (2000), in most instances, minibus services compete with rather than complement formal bus and rail services. There are two types of competition. First, there is the head-to-head competition with conventional public transport buses along popular routes, effectively duplicating the routes. Paratransit buses arrive at the stop just before the conventional one taking away passengers by offering a faster trip. Second, there is the complementing type of competition. This happens if headways of the fixed-schedule bus are too long and the paratransit vehicle fills in the gap, shortening the effective waiting time.

Most case studies obtained by personal communication and presented by Cervero (2000) indicate that paratransit services are mainly organized as cooperatives operating 8-15 seater minibuses on fixed routes. Most of the services run in direct competition to a public transport system of a public transit authority. The approach presented in this paper will be based on those most common characteristics.

3 Proposed model

The proposed model enhances the multi-agent simulation MATSim (2011). At this point, only a brief overview of the software tool MATSim with regard to this paper can be given. Please refer to Balmer et al. (2005) or Raney and Nagel (2006) for an in-depth description of MATSim. Rieser and Nagel (2009) and Rieser (2010) describe the public transport capabilities of MATSim in general and Neumann and Nagel (2010) with focus on its application.

In MATSim, each traveler of the real system is modeled as an individual agent. Initially, all agents independently generate daily plans that encode among other things their desired activities during a typical day as well as the transportation mode. Agents typically have more than one plan; in the present investigation, they are restricted to one plan only. The original approach consists of an iterative loop that has three steps:

- Traffic flow simulation (synthetic reality): All selected plans are simultaneously executed in the simulation of the physical system.

- Scoring: All executed plans are scored by a utility function.

- Learning: Some agents are allowed to modify their plan.

The current simulation offers the modes walk, bike, car and public transport. The simulation features an integrated model in the way that an agent can have different legs in its plan, each using a different mode of transportation. In the approach used here, an agent using public transport can use minibus services as well as formal services. Minibus services are transparently integrated into the public transit schedule, implying that the model assumes that paratransit operators announce their schedule beforehand. As route search is based on the schedule, trips using formal public transit in combination with paratransit can be found, allowing for multiple transfers. Although a minibus may not be on time, the general frequency of the service is registered.

The route planning by the passenger is similar to a schedule-based transit assignment. That is, paratransit is included in the passenger's route plan by the assumption that there will be a certain minibus at a certain stop at a certain time. Especially with minibuses ignoring the timing of their schedule and driving as fast as possible, the minibus may be far away from its schedule. However, for typical minibus services running at high frequencies, this is not a serious issue since the passenger will just take the first approaching minibus heading to the desired destination.

With the addition of paratransit, the current default version of the MATSim public transit passenger router (Rieser and Nagel, 2009; Rieser, 2010) searches the time-minimizing connection for each agent using a combination of public transport, minibus service and walking with respect to access and egress walks, waiting time and transfers, i.e. the additional penalty for a line switch is equivalent to an additional 60s of travel time. Fare does not play a role in that version of the router. See Moyo O. and Nagel (2012) for experiments with more realistic routing.

MATSim involves learning iterations on the side of the passengers. In order to save computing time, in any given iteration this is restricted to 10 % of the agents searching for an alternative route. Passengers will then stick to that route for the following iterations until they are selected for replanning again. The execution of passengers' plans is scored in order to test for relaxation of the system, but in contrast to standard MATSim the scores are not used for anything else. For that reason, the precise mathematical form of the scoring function is omitted to not distract from the main focus of the paper.

3.1 The general paratransit system

As described in section 2, many paratransit services serve a corridor by plying a fixed route. For the proposed model, it is assumed that each route can be seen as a paratransit *line* operated by one cooperative (operator).

At the beginning, each operator starts with one *line* determined by two randomly picked links and two shortest paths connecting both links with each other. The resulting circular *route* is operated from a randomly picked start time to a randomly picked end time by one vehicle (minibus). Minibuses are assumed to run without breaks during their time of operation; it is assumed that some kind of crew scheduling makes this possible. Stops are located at every intersection, thus allowing boarding and alighting near any node of the network. A *line* serves every stop that it passes.

Minibuses ply the same streets as buses and private cars. All types of vehicles interact in the way that congestion affects every type of vehicle, and minibuses and buses can be caught in a traffic jam as the private car user does. Minibuses can overtake each other and other buses at stops. A minibus fully loaded will not try to pick-up additional passengers and instead proceed as fast as possible to the next stop determined by one of the passengers' desire to alight. A minibus with empty seats left will ask the waiting agents at each stop it passes by for their destination. If the minibus serves that stop, it will pick up the agent, otherwise not.

The model allows for different modes of operation. Transit vehicles and minibuses can a) be forced to circulate strictly according to the schedule. A delayed vehicle will try to run as fast as possible to catch up with the schedule. Vehicles can b) be forced to await departure time at certain stops only. Finally, the vehicles can c) be allowed to drive as fast as possible eventually ignoring the timing information in their schedule. In this paper, mode a) is applied to formal public transit and mode c) for minibus services.

3.2 Scoring of the paratransit operators

Scoring takes place at the end of the day (iteration). The $score$ of one operator consists of income inc and expenses exp.

$$score = \sum (inc - exp) \tag{1}$$

Income is generated by collecting fares. The fare system allows for lump sums $f_{boarding}$ [¤], distance-based fares f_{km} [¤/km] and combinations of both. With l [km] being the trip length of one passenger and N_{pax} being the number of passengers of the operator, the income for each operator is calculated as

$$inc = \sum_{i=0}^{N_{pax}} (f_{boarding} + f_{km} \cdot l_i) \tag{2}$$

Expenses consist of fixed costs and distance based costs. Fixed costs c_{fix} [¤] cover expenses related to the vehicle, e.g. official operating license and driver. Distance based costs c_{km} [¤/km], e.g. fuel, are summed up for each kilometer traveled by the operator's vehicles. With m [km] being the distance traveled by one vehicle and N_{veh} the number of vehicles owned by the operator, the operator's expenses are calculated as

$$exp = \sum_{i=0}^{N_{veh}} (c_{fix} + c_{km} \cdot m_i) \tag{3}$$

The total score of one operator can be seen as the operator's (net) cash flow. Profitable operators/*lines* end up with a positive cash flow, non-profitable *lines* with a negative cash flow. At the end of the iteration, the cash flow is added to the budget of the operator.

3.3 Optimization process

Since a paratransit *line* is operated by one operator, each operator tries to improve its own *line*. There is no explicit coordination or cooperation between the operators, except for the fact that an agent using paratransit can transfer to a different paratransit *line*. Different operators together can thus form a hub if this emerges from the optimization process, but otherwise are engaged in competition provided that the model's franchise system allows for that. The franchise system prevents two operators from providing the exact same services. However, the system allows two operators to ply the same route, but with different termini. Therefore, an operator providing a slightly better route without additional transfers in between can oust the first operator from the market.

Optimization of the paratransit operators takes place in parallel with the passengers' adaptation process. In every iteration, the following happens:

1. The paratransit adaptation module is run as described below. This will result in a new (pseudo-)schedule for public transit.

2. A randomly selected 10% of passengers (agents) obtains a new route based on that (pseudo-)schedule, computed as described earlier. The other 90% of passengers remain on their existing route for this iteration.

3. The traffic flow simulation (synthetic reality) is run with those paratransit operators and passengers.

That is, for the present paper the passengers do not optimize beyond what is described in item 2. This means that they do, in fact, not react to the *actual* schedule, or to congestion including denied boarding.

At the beginning of each optimization step, an operator may have to compensate for a imbalanced budget by selling minibuses. For each minibus sold, a lump sum is added to the budget. If no minibuses are left, the operator is shut down and another one is initialized with one minibus for free. If the operator is not shut down, it can try to optimize its current plan. This can be done by altering:

The vehicle fleet An operator can buy new minibuses from the budget for a lump sum. The lump sum for buying a minibus is the same as for selling one. The operator can buy as many minibuses as possible. If the operator has insufficient funds, it can save the budget for the next iteration. More minibuses directly translate into higher frequencies. A positive budget implies a positive cash flow at previous iterations. By buying new minibuses the cash flow can become negative, which may result in a negative budget. This is compensated by the possibility to sell minibuses at the start of the next iteration. As a result, the number of minibuses owned by the cooperative should fit the market restrictions, i.e. the cash flow is balanced and the number of minibuses becomes stable.

The time of operation An operator can increase the time of operation by changing the time of the first or the last planned departure. The first departure can, for example, be set to 6 o'clock instead of the initial randomly chosen 8 o'clock. Since the operator does not know the potential demand between 6 and 8 o'clock, the time adaptation is tested with a second *line*, which operates the same *route* with one single test vehicle taken from the original *line*. If the original *line* has only one vehicle, the operator cannot alter the time of operation. At the beginning of the next iteration both *line*s are scored and the cash flow is compared against the one from the last iteration. If cash flow increased, the time adaptation is considered to improve the plan and the plan is changed accordingly. Otherwise, the adaptation is dropped. In both cases the second *line* is shut down and the test vehicle is transfered back to the original *line*.

Alternatively, an operator can decrease the time of operation by analyzing the demand of the last iteration. The start time is then set to the time of the first passenger boarding one of his vehicles and the end time is set to last passenger alighting. This can compensate for slack periods, minimizing the expenses of empty minibuses circulating. Since the vehicles need some time to get from and to the depot, the time of operation is increased by about 15 minutes on both ends.

3.4 Additional aspects

The number of operators can either be fixed to a certain number or be determined by a given share of operators with a positive cash flow. The latter version will not only replace operators who went bankrupt, but will also start to create additional operators. If the share, for example, is set to 50 % and three out of four operators run a profitable business, the total number of operators will be increased by two. If there is only one out of five operators running a profitable business, the total number of operators will be decreased by three. Without this, the mutation of the system would come to a halt whenever every operator has found a profitable *line*. With the dynamic adaptation enabled the mutation decreases slowly, eventually coming to a rest when no market niche is left. This can be seen as some sort of simulated annealing.

Since the number of passengers allowed to search for a new route in each iteration is restricted to 10%, it can become difficult for new operators to accumulate enough passengers from the start to stay in business. Therefore, newly found cooperatives can be excluded from scoring for a set number of iterations. This is a configurable parameter (see Sec. 4) which can be seen as an investor balancing the budget for an initial period.

4 Application

The proposed paratransit approach is tested with three different scenarios. All use the same multi-modal network introduced in Neumann and Nagel (2012) and shown in Figure 1. It contains 16 nodes connected by 48 car links, each with a length of 1200 meters and a capacity of 2000 vehicles per hour. Each car link can be referred to by taking its start and end node's name, e.g. the link from node 14 to node 13 is called 1413, the corresponding back link 1314 respectively. The speed-limit is set to 7 meters per second to compensate for traffic lights and other obstacles. Four additional car links, called A, B, C and D, are included to locate demand at the nearby nodes directly. These links have a length of 100 meters and a speed-limit set to 100 m/s. Capacity is set to infinity. Since the links A to D loop, the actual coordinate of the passengers located on those links is identical with the one of the nearby node, e.g. node 14 for demand of link A. The minibuses used in this paper have a capacity of 11 seats allowing to carry 10 passengers and the driver. Since they ply on the car links, they are subject to the restrictions of these links. The minibuses stop at the end of each link. This allows for transfers at the node, since every incoming link is a possible paratransit stop. For each person boarding, the minibus is delayed by 2 seconds, for each person alighting, the minibus is delayed by 1 second.

Furthermore, there is one train line running from node 1 via node 2 to node 3 and back via node 2 to node 1, marked with a dashed line in Figure 1. The transit schedule allows for one round trip in about 15 minutes and the train stops at each stop for at least

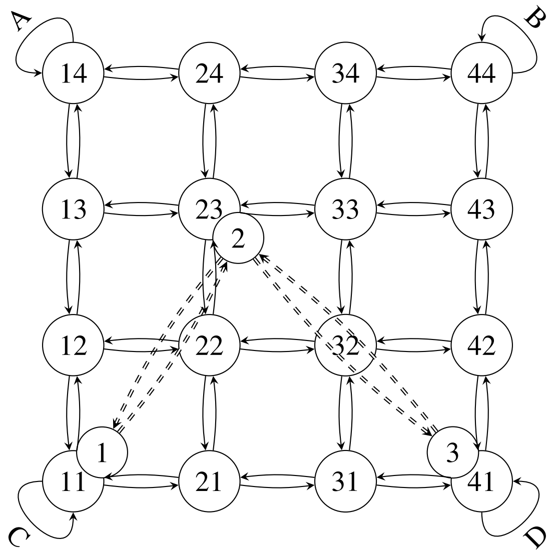


Figure 1: Multi-modal network with one transit line (dashed line)

15 seconds. The first train starts at 5 o'clock and then every 5 minutes until the last one departs at 13 o'clock. The capacity of the train is set to 100 passengers per train; the delay per person boarding or alighting is set to half a second. On the connection from C to D, the train is about 20% faster than the minibus. Conversely, minibuses tend to run more often than the train. Since the travelers' departure times are fixed, the shorter waiting time for the minibus may compensate for the longer travel time, and the traveler may select the minibus.

In each scenario, a minimum of ten separate operators are allowed to operate paratransit lines, in addition to the train. It is expected that not every operator will run profitably, since demand may not be sufficient. The target share of profitable operators is set to 50 %. Therefore, the total number of operators will be increased if there are more than five profitable operators in play, and reduced if there are fewer. All three scenarios have the same configuration, except for the schedule of the train (see below), and run each 10000 iterations. Passengers are only allowed to change their route, but not the transport mode. This allows to change to different paratransit lines, to the train, or to walk directly in case this is the least cost path. Passengers determine the least cost path with regards to walking time – e.g. to and from stops –, in-vehicle travel time, transfer time, waiting time, and line switch cost. Additional monetary costs for the passengers like fares are not included in this paper. The operators pay 10 monetary units [¤] per day for every minibus they own. This prevents the operators from running a *line* for very short periods of the day. Furthermore, they have to pay 0.30 ¤ for each vehicle kilometer. Revenue is 0.075 ¤ per passenger kilometer. Therefore, an operator needs approximately an average load of 50 % to run a profitable business, i.e. 4 passengers to balance the running costs, and at least one additional passenger to make enough profit in order to pay for the fixed costs. The price of a minibus is set to 1000 ¤, regardless whether bought or sold. At the end of each iteration, 10 % of the passengers are allowed to search for a new route. Newly found operators have 3 iterations to break even, thus allowing to attract up to 27.1 % of the possible demand by the end of the third iteration. During that time they will at least once fit their time of operation to the actual demand.

During replanning, the operator's probability to increase the time of operation by trying a new first or last departure time is 5 % each. The probability to decrease the time of operation by setting the first and last departure time according to demand is 40 %. 50 % is the probability to buy new vehicles.

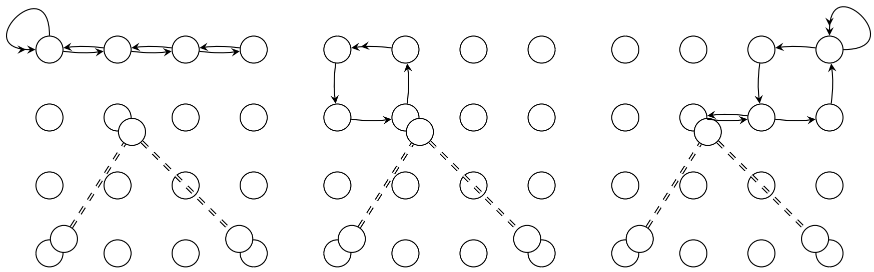
Each scenario features the same demand of 1000 trips for every origin-destination combination of ABCD, resulting in a total of 12'000 trips. The passengers' departure time is uniformly distributed between 6 and 10 o'clock.

The schedule of the train is altered in each scenario. In the first scenario, the train will depart every minute. In the second scenario, the train departs every 10 minutes and in the last scenario, the train departs every hour only.

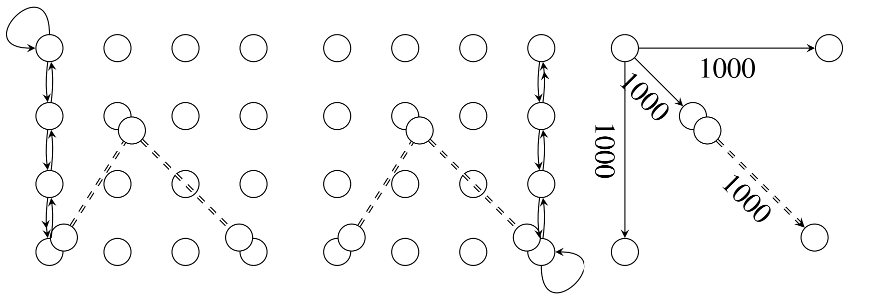
In the first scenario, the train departs every minute. Figures 2a to 2e show the routes of the five operators serving any passengers. The route of the train is always marked with a dashed line, regardless whether serving passengers or not. One can distinguish two different types of operators. Operator 1, 4 and 5 serve direct connections, whereas the operators 2 and 3 act as feeders to the train. There is no operator operating in direct competition to the train, especially no diagonal line has evolved. The flow from each origin A-D to the corresponding destination links are shown in Figures 2f to 2i. With the exception of the demand B-A and D-A, all trips of one relation use the same route. In case of the demand B-A (Fig. 2g), two agents choose to transfer at A from operator 1 to operator 4, whereas the majority of 998 agents opts for feeder service and changing to the train. A similar behavior can be found in Figure 2i, where two agents take the train from D to C and transfer to the line of operator 4. Due to the low probability of 10 % to search for a new route, some agents will stick to non optimal routes. This can be seen as realistic behavior, where some passengers stick to the routes they know, unaware of better alternatives.

As mentioned before, the loop links A to D do not influence the cost function, since they have no physical impact. Hence, the routes found can be seen as optimal route for the given demand. The terminus of each route is located on a link which does not force the agents to transfer. All five operators have a similar time of operation which fits the given demand. The number of vehicles per operator correlates with the number of links of the operator's route. This is about two vehicles per link for all five operators. The last route is found by operator 5 in iteration 1697. Later iterations only further improve vehicle fleet size and time of operation, but do not change the paratransit network. This can be seen from a) the average score of the agents, b) the number of profitable operators, and c) the number of vehicles of those operators, which all remain stable in later iterations, see Figure 3a.

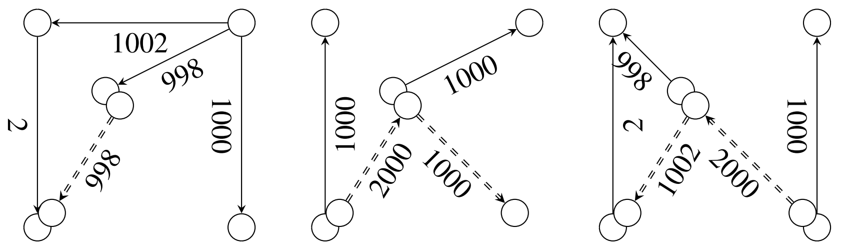
In the second scenario, the train departs every 10 minutes. The results are shown in Figure 4. In contrast to the first scenario, the feeders to the train are missing. As in the first scenario, the demand going from C to D and vice versa still takes the train, but



(a) Route of operator 1 (b) Route of operator 2 (c) Route of operator 3



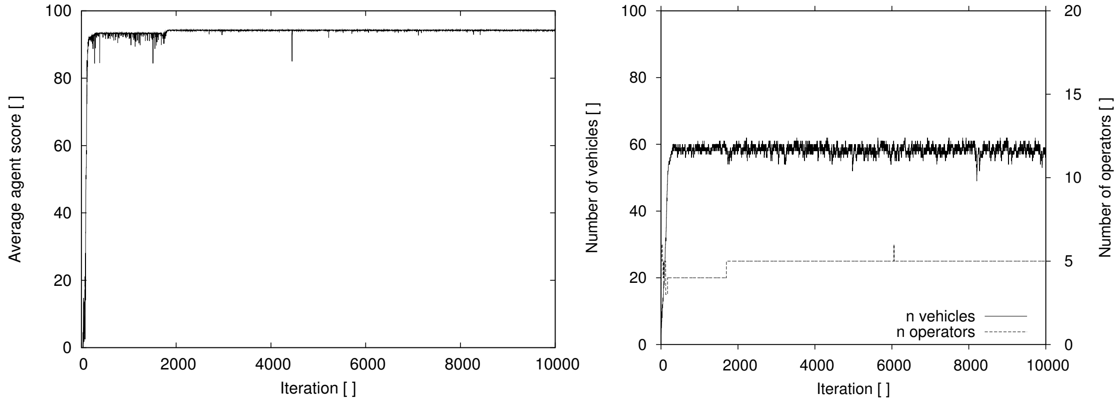
(d) Route of operator 4 (e) Route of operator 5 (f) Trips from origin A



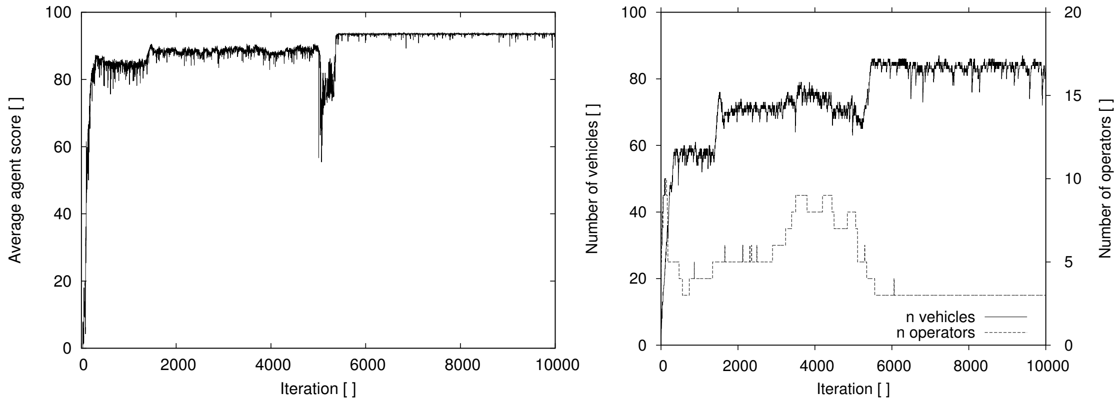
(g) Trips from origin B (h) Trips from origin C (i) Trips from origin D

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:00	13	2002	0
Operator 2	06:00-10:00	9	1998	8
Operator 3	05:45-10:15	11	1998	77
Operator 4	05:45-10:15	12	2004	170
Operator 5	05:45-10:15	13	2000	1697

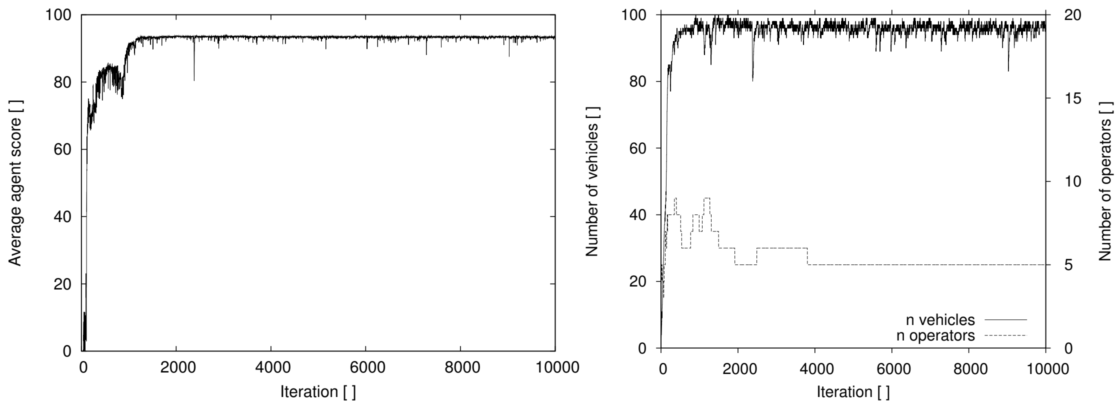
Figure 2: Resulting routes and flows of scenario 1min - Double arrows indicate termini



(a) First scenario - 1min



(b) Second scenario - 10min



(c) Third scenario - 60min

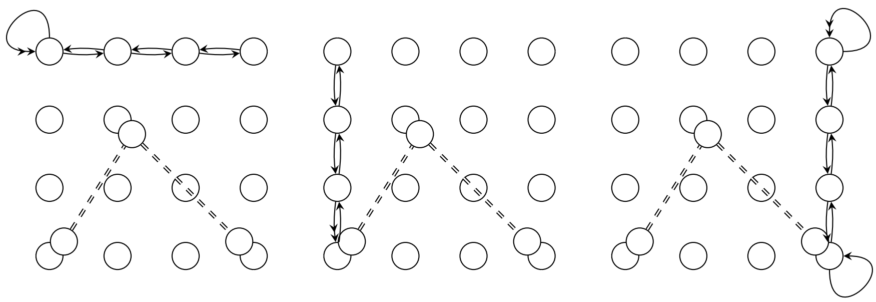
Figure 3: Average score of the passenger agents, the number of operators with profit and the number of their vehicles for each iteration - Scenarios 1min, 10min and 60min

the demand going diagonally is now using one of the three paratransit lines. However, some of the agents going diagonally use a combination of train and minibus. But still, the majority transfers from one paratransit line to another, e.g. 847 agents going from A to D use paratransit only and 153 use a combination of train and paratransit. The four additional trips shown in Figure 4e use paratransit as well. The operator of the route used is not shown here. The operator was found in iteration 9999 and managed to attract some of the demand during the last two iterations. Nevertheless, the demand is insufficient to stay in business and the operator would have been shut down in the following iteration. The six trips shown in Figure 4f use the very same operator. All operators have the same time of operation and all operators serve the same amount of trips compared to the number of vehicles possessed.

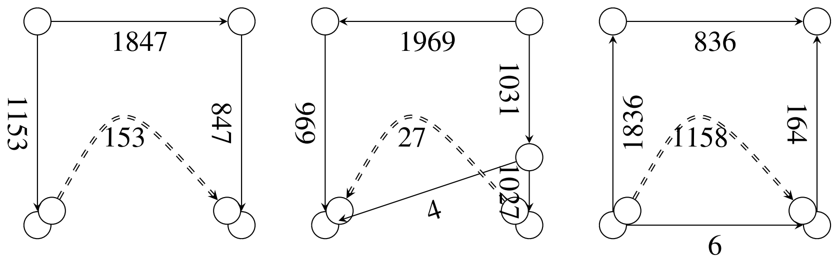
What happens if an operator with a superior route enters the market can be seen in Figure 3b. First, the cutthroat competition of too many operators with inadequate routes yields to a deterioration of paratransit services, i.e. the number of vehicles decreases slowly until the average agent score drops significantly. In iteration 5292, operator 3 enters the market attracting more passengers with his route than his vehicle fleet can initially handle. In the following iterations operator 3 starts buying new vehicles as fast as he can afford. Meanwhile, some of the other operators go bankrupt, due to the change in demand. With fewer operators in play, the final solution can maintain more vehicles and results in a higher average agent score.

In the third scenario, the train departs every hour. Again, Figure 5 does not show any feeders, but this time one operator runs in direct competition to the train (operator 3), and one operator managed to establish a diagonal line (operator 2). Due to the low frequency of the train, the majority of the demand going diagonally and from C to D and vice versa uses now minibus services. The train has nearly no demand left. The relation B-D is entirely served by minibuses. In contrast to passengers traveling from B to D, passengers going from D to B have to transfer once at node 42, since the terminus of operator 4 is located on link 4142, see Figure 5d. At iteration 9998, a newly found operator is serving a similar route. This route is longer than the route of operator 4 and the new operator will not sustain, but the important thing is, that he offers a direct connection from D to B without any transfers. Consequently, some passengers switch to this new option, i.e. 4 passenger transfer at a later point at node 43, and 40 do not transfer at all using minibuses of the new operator only. 956 passengers stick to the old solution, which is a direct result of the restricted rerouting opportunity of 10 % per iteration.

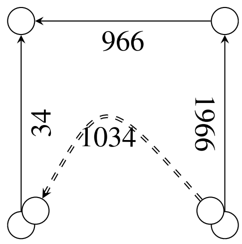
For further comparison, Figure 6 shows some key figures for the three different scenarios shown here and some additional scenarios included in the appendix, please refer to Figures 7 to 11. All values are standardized. For example, the number of trips served by train has a maximum of 6000 trips, which equals 1.0. The minimum is 71 trips, which equals 0.0. Note the correlation between the train's frequency and the number of trips served by the train. With the train loosing passengers, minibus services gain in passengers and passenger-kilometers. Although one would expect a monotonically decreasing/increasing of both curves, this is not mandatory. The number of trips served depends on the number of passengers entering a vehicle. Thus, more transfers translate into more trips. For example, the scenario 20min has more passengers using both train



(a) Route of operator 1 (b) Route of operator 2 (c) Route of operator 3



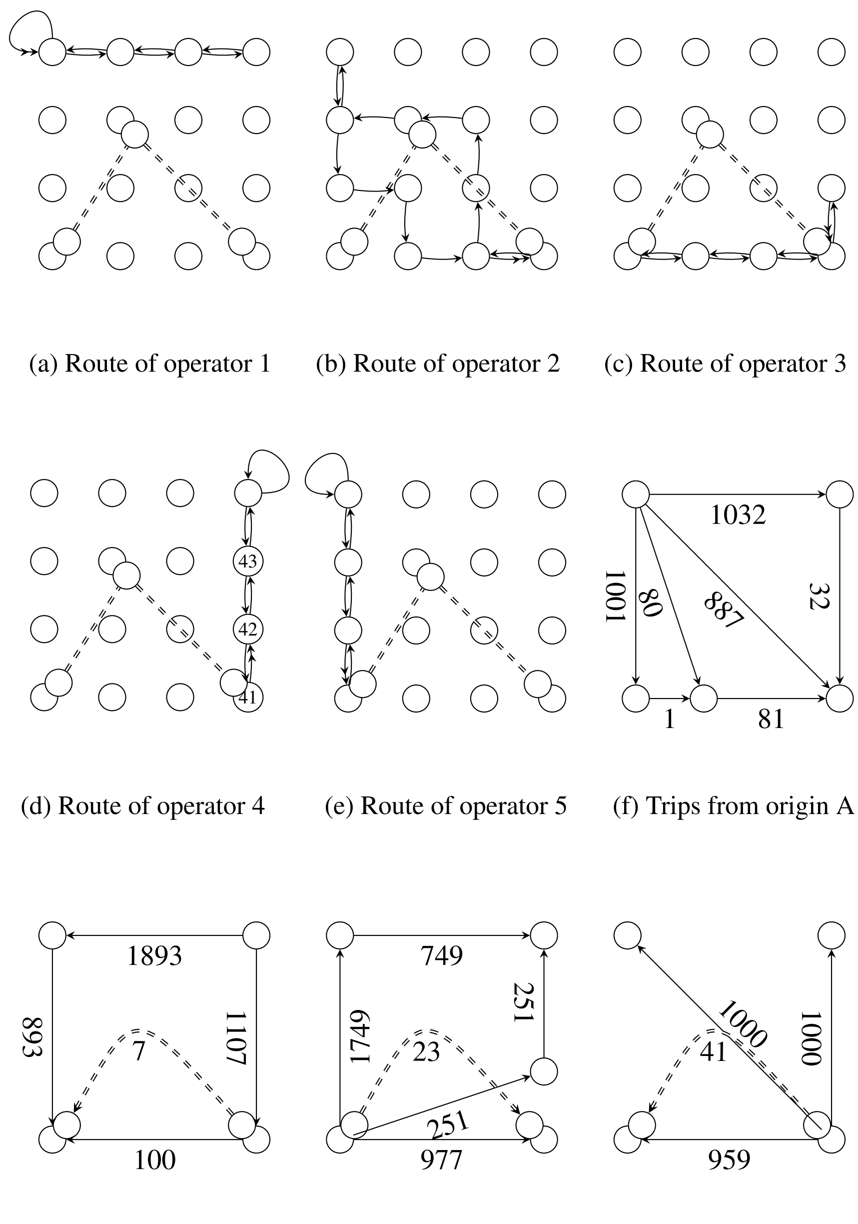
(d) Trips from origin A (e) Trips from origin B (f) Trips from origin C



(g) Trips from origin D

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:15	34	5618	0
Operator 2	05:45-10:15	25	3992	1339
Operator 3	05:45-10:15	24	4008	5292

Figure 4: Resulting routes and flows of scenario 10min - Double arrows indicate termini



(a) Route of operator 1 (b) Route of operator 2 (c) Route of operator 3

(d) Route of operator 4 (e) Route of operator 5 (f) Trips from origin A

(g) Trips from origin B (h) Trips from origin C (i) Trips from origin D

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:30	22	3674	0
Operator 2	05:30-10:15	23	1968	0
Operator 3	05:30-10:15	16	3259	72
Operator 4	05:45-10:15	12	2285	829
Operator 5	05:45-10:15	22	3643	2491

Figure 5: Resulting routes and flows of scenario 60min - Double arrows indicate termini

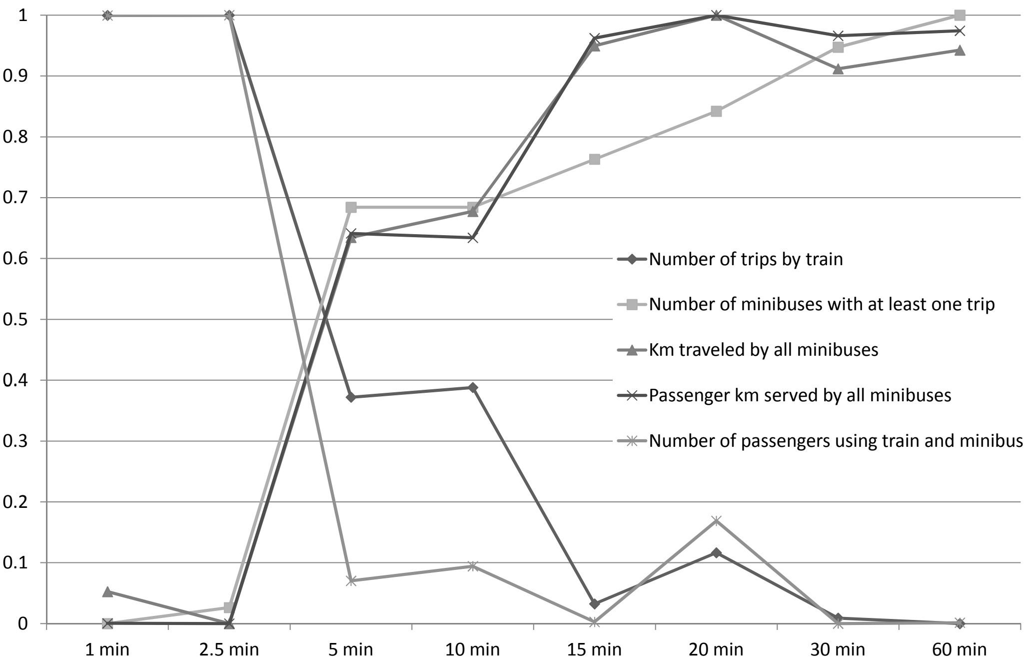


Figure 6: Key figures for the scenarios 1min, 10min and 60min as well as additional scenarios included in the appendix - All values are standardized with 0 being the minimum and 1 being the maximum

and minibus than the scenarios 15min and 30min, resulting in the highest total number of minibus trips. Nevertheless, the solution found in 30min may be better in terms of transfers. A good indicator for the quality of the solution from the minibus point of view is the number of minibuses serving at least one trip, i.e. minibuses from operators subject to go bankrupt are not considered. The minibus fleet is monotonically increasing implying that a declining service frequency of the train, allows the minibus operators to put more minibuses into service. This derives from the current implementation of the model, which forces minibus operators to buy as many vehicles as they can afford.

5 Conclusion and Outlook

Despite the fact that the proposed model works for illustrative scenarios there are still some caveats. First, the route searching algorithm itself is heavily based on randomly drawn routes and therefore depends on the random seed. The current implementation of the model is deterministic in the sense that the same input data and random seed results in the same simulation results. However, a different random seed will change the output. For example, the iteration in which a route is found will be different, and probably the same route will be found but the terminus will be on a different link. It is even possible, but unlikely, that in the third scenario ("60min") no diagonal route evolves. If such a route is never picked by chance, it cannot be tested and hence cannot be in the results.

Second, the passengers' decision is based on travel times only. This may put minibus services in a more favorable position compared to the train due to lower expected waiting times. However, this often comes with higher fares. Thus, the model should integrate fare into the scoring of the agents as well as in the route choice algorithm. MATSim's current implementation of mode choice already allows agents to change mode, e.g. from car to public transport and paratransit respectively. However, that solution still lacks an agent scoring function which incorporates the monetary expenses related with the mode. Recent research looks into this for formal public transit (Kickhöfer et al., 2012, forthcoming). That model could then be incorporated to a real world scenario like the Berlin scenario available at VSP TU Berlin (Neumann et al., 2012).

From the operator's side, the proposed model can be further developed by a series of optimization strategies. First, a new stop at the beginning or the end of the existing *route* could be added. The new stop must not form a loop or u-turn and should be in the general direction of the existing *route*'s corridor. Second, the *route* could be shortened by removing stops at the end of the *line* with no demand at all. A *line* could also be split if demand concentrates on two independent segments of the *route*. Effectively, this would form an operator within an operator thus allowing for subsidiary companies.

Further possible enhancements adopt mechanisms from real-world paratransit examples. For example, there are minor detours. Instead of only picking-up agents with a destination served by the predefined *route*, the minibus driver could consider to incorporate a small detour. The minibus would then deviate from its *route*, deliver the new agent and return to the *route* at the point of the next stop, defined by one of the in-vehicle passengers' destinations. If that detour is no longer than, for example, 1.5 times the predefined *route* to that stop, the agent would be picked-up. Otherwise, the minibus would proceed as planned.

Another form of adapting the predefined *route* would be adding short turning. If a minibus could make more profit in the opposite direction, it would make a u-turn going the opposite direction. The minibus driver would have to check waiting passengers on the opposite link of the network. In Kingston, Jamaica, drivers were known to force passengers out of their vehicle, then running in the opposite direction (Talvitie, 1999). In Damascus, Syria, passengers may be asked to change for the next vehicle if load can be optimized by concentrating. The next vehicle will depart immediately and passengers get a fare refund of the first one.

Another strategy are equal headways, instead of operating according to schedule or circulating as fast as possible. This mode of operation is known for slack periods in cities of Turkey, where drivers tend to delay departure in order to avoid bunching. This allows for more passengers to accumulate along the route. The operator could then adapt the frequency according to demand reported by its vehicles. The same mode of operation can be applied to formal bus lines with high frequencies and is already implemented in MATSim (Neumann and Nagel, 2010).

To conclude, some of the proposed enhancements are currently in development in order to apply the approach to real world scenarios of two different applications. The first scenario deals with the network design optimization of a public transit authority which needs to refit its network to meet the requirements of a changed demand. The second one focuses on simulating real paratransit systems and their interaction with formal public transit. This will provide a better understanding of transport systems to the policy makers and other stakeholders.

Acknowledgments

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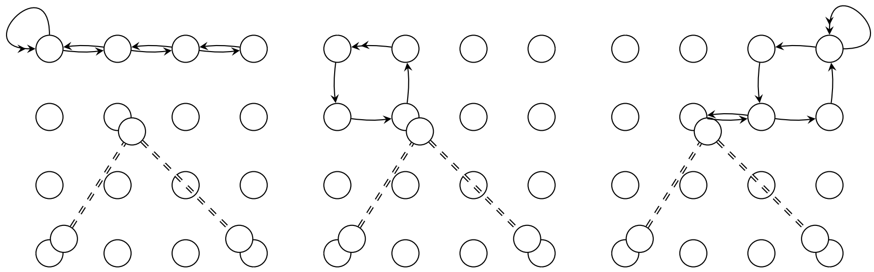
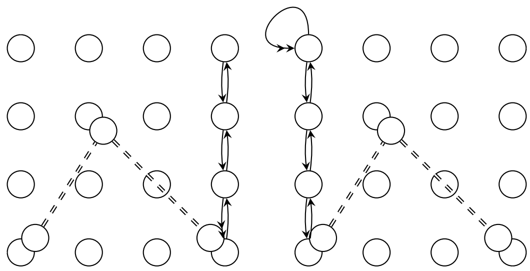
A Results of additional scenarios

The scenarios shown here were simulated with the same input data as the three scenarios 1min, 10min and 60min discussed earlier. Again, only the transit schedule of the train was modified. The scenarios include train schedules with headways of 2.5min, 5min, 15min, 20min and 30min. The resulting routes are shown in Figures 7 to 11. These figures include the same details about the operators in business, but the actual passenger flows are not shown here, since they were not analyzed in detail. In addition, Figures 12 and 13 show the average agent score, the number of profitable operators and the number of their vehicles for the scenarios not discussed earlier.



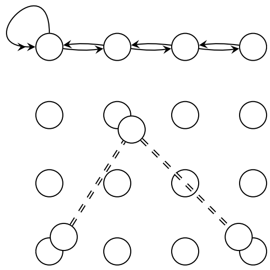
(a) Operator 1 (b) Operator 2 (c) Operator 3



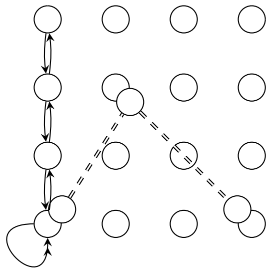
(d) Operator 4 (e) Operator 5

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:15	11	2000	0
Operator 2	06:00-10:15	9	2000	8
Operator 3	05:45-10:15	13	2000	77
Operator 4	05:45-10:00	13	2000	1035
Operator 5	05:45-10:15	13	2000	1071

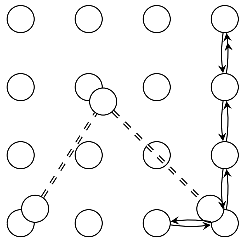
Figure 7: Resulting routes of scenario 2.5min - Double arrows indicate termini



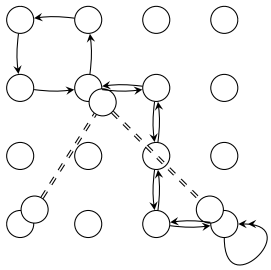
(a) Operator 1



(b) Operator 2



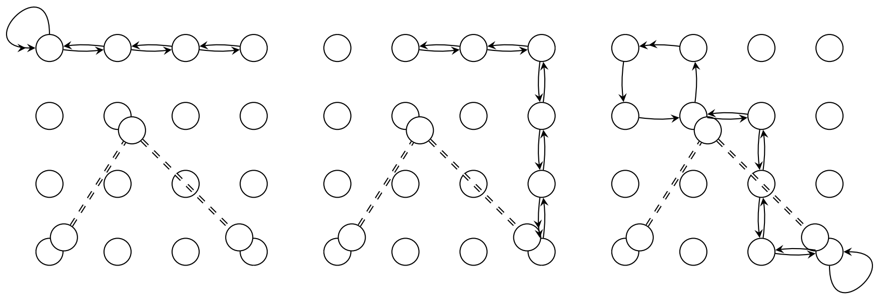
(c) Operator 3



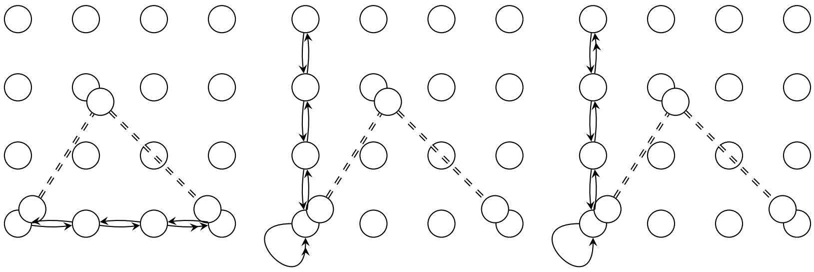
(d) Operator 4

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:15	23	3873	0
Operator 2	05:45-10:15	24	3858	4229
Operator 3	05:45-10:15	13	2161	4346
Operator 4	05:30-10:15	23	1981	5409

Figure 8: Resulting routes of scenario 5min - Double arrows indicate termini



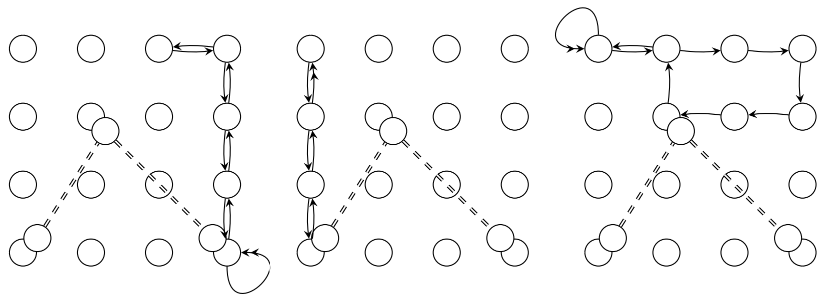
(a) Operator 1 (b) Operator 2 (c) Operator 3



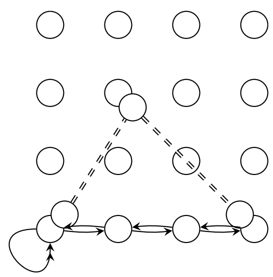
(d) Operator 4 (e) Operator 5 (f) Operator 6

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:45	22	3999	0
Operator 2	05:30-10:45	11	2022	77
Operator 3	05:30-11:00	18	1875	329
Operator 4	05:45-10:45	11	1865	767
Operator 5	05:45-10:15	6	1009	2415
Operator 6	05:45-10:15	19	3095	3418

Figure 9: Resulting routes of scenario 15min - Double arrows indicate termini



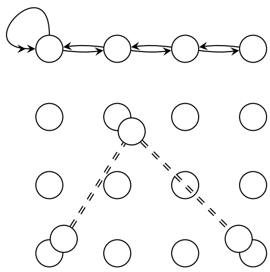
(a) Operator 1 (b) Operator 2 (c) Operator 3



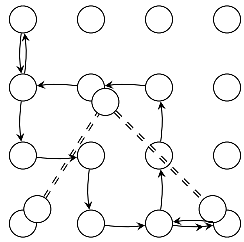
(d) Operator 4

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-12:00	14	2659	964
Operator 2	05:45-10:15	29	4693	1093
Operator 3	05:45-10:30	28	3877	1288
Operator 4	05:45-12:00	19	3996	2058

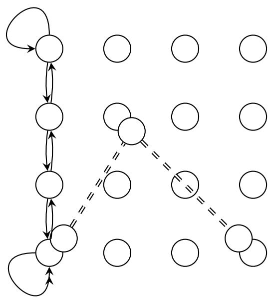
Figure 10: Resulting routes of scenario 20min - Double arrows indicate termini



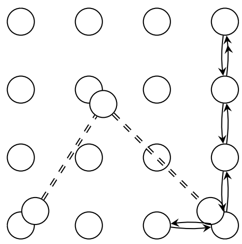
(a) Operator 1



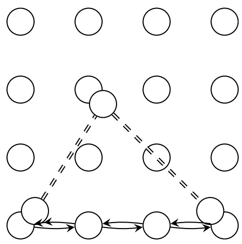
(b) Operator 2



(c) Operator 3



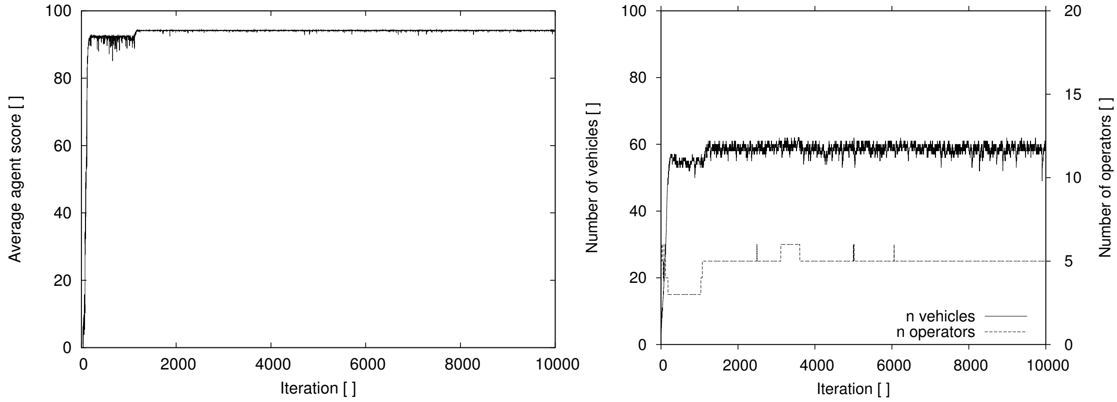
(d) Operator 4



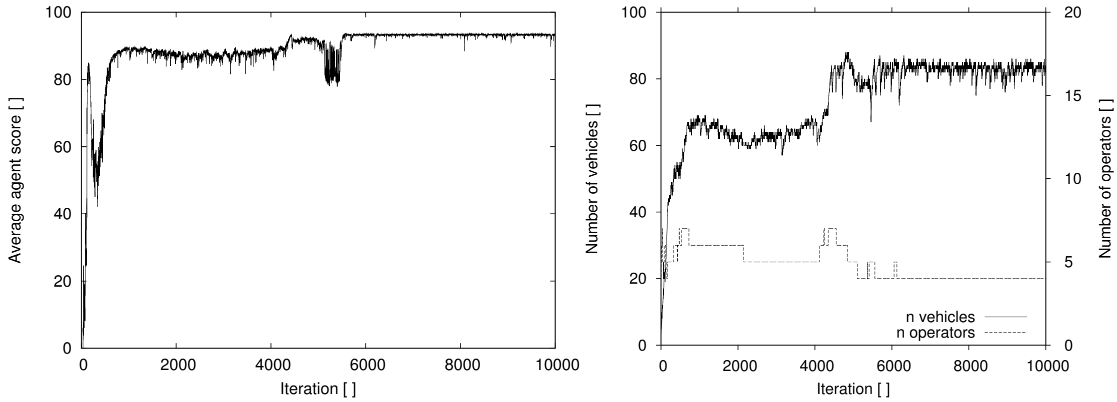
(e) Operator 5

	Time of Operation	Vehicles	Trips	Iteration
Operator 1	05:45-10:30	24	3969	0
Operator 2	05:30-10:15	23	1940	0
Operator 3	05:45-10:15	23	3963	589
Operator 4	05:45-10:45	12	2099	4346
Operator 5	05:45-10:30	12	2016	5994

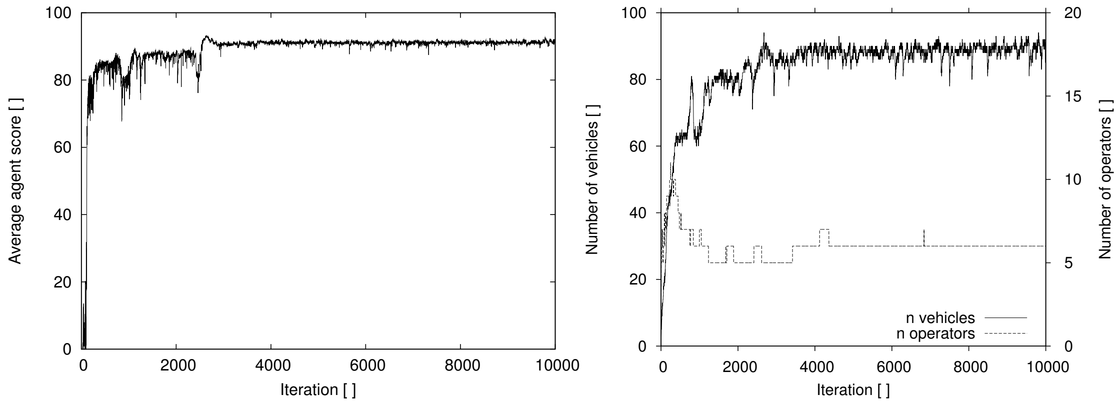
Figure 11: Resulting routes of scenario 30min - Double arrows indicate termini



(a) Scenario 2.5min

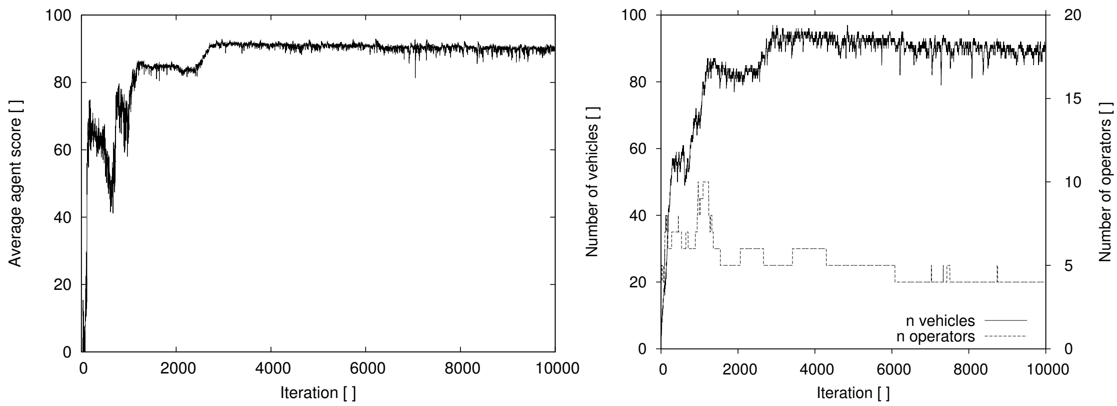


(b) Scenario 5min

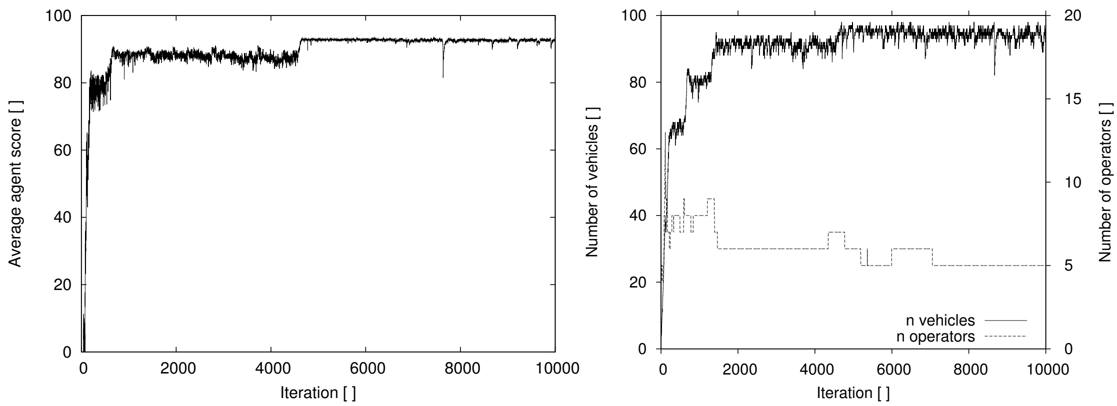


(c) Scenario 15min

Figure 12: Average score of the passenger agents, the number of operators with profit and the number of their vehicles for each iteration - Scenarios 2.5min, 5min and 15min



(a) Scenario 20min



(b) Scenario 30min

Figure 13: Average score of the passenger agents, the number of operators with profit and the number of their vehicles for each iteration - Scenarios 20min and 30min