



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.

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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 operator's side, a transit line can be optimized by optimizing its headways and stop spacing [1], its service frequency and bus size [2] or by combining limited-stop services with high-frequency unscheduled services [3]. Optimization should consider the interrelation with other transit lines, that is, optimization of one single transit line may induce deterioration of quality of another line. Thus, network design and its optimization has been studied (e.g. [4]). Further examples of optimizations focus on meeting the demand of a given OD-matrix [5], or on feeder services [6, 7] and their interaction with a rail transit line [8].

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 [9], feeder-corridor systems [10] and integrated systems based on a hierarchy of specialized services that complement and coordinate their operations [11]. 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. 12, 13, 14, 15]. A common topic in such investigations is under which circumstances cooperative structures can emerge despite the competition [e.g. 16]. 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*.

2. Proposed model

Traveler model and integration with MATSim. In MATSim [17], 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 transport 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: (1) Traffic flow simulation (synthetic reality): All selected plans are simultaneously executed in the simulation of the physical system. (2) Scoring: All executed plans are scored by a utility function. (3) Learning: Some agents are allowed to modify their plan.

The current simulation offers the modes walk, bike, car and public transport. Each agent can have different legs in its plan, each using a different mode of transport. 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, as if 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, this is not a serious issue, since minibus services typically run at high frequencies, and the passenger will just take the first approaching minibus heading to the desired destination.

In order to save computing time, in any given iteration the “passenger learning” 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 can be omitted here.

The general paratransit system. For the proposed model, it is assumed that each route can be seen as a paratransit *line* operated by one 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.

Scoring of the paratransit operators. Scoring takes place at the end of the day (iteration). The *score* of one operator consists of revenue *rev* and expenses *exp*: $score = \sum (rev - exp)$. Revenue is generated by collecting fares. The fare system allows for lump sums $f_{boarding}$ [€], distance-based fares f_{km} [€/km], and combinations of both. 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.

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.

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 can oust the first operator from the market.

Optimization of the paratransit operators takes place in parallel with the passengers' adaptation process. At the beginning of each iteration, an operator may have to compensate for an 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: (a) *The vehicle fleet*: Operators with sufficient leftover funds from the previous iteration buy additional minibuses. (b) *The time of operation*: An operator can increase the time of operation. 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, this is implemented by a trial-and-error procedure. 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.

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. This is the version used for the present paper.

3. Application

The proposed paratransit approach is tested with eight different scenarios, with two of them illustrated in more detail in this paper. All use the same multi-modal network introduced in [18] and shown in Figure 1a. It contains 16 nodes connected by 48 car links, each with a length of 1200 meters and a capacity of 2000 vehicles per hour. 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, a speed-limit of 100 m/s, and a flow capacity of infinity. Since these links loop, the actual coordinates of the passengers located on those links are identical with those of the nearby node. 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.

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 1a. Trains run between 5am and 1pm; the train frequency is varied (see below). The capacity of the train is set to 100 passengers per train. 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, operators are allowed to operate paratransit lines, in addition to the train. The target share of profitable operators is set to 50%. All three scenarios have the same configuration, except for the schedule of the train (see below), and each runs 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, and 0.30¤ for each vehicle kilometer. Revenue is 0.075¤ per passenger kilometer. Therefore, an operator needs approximately an

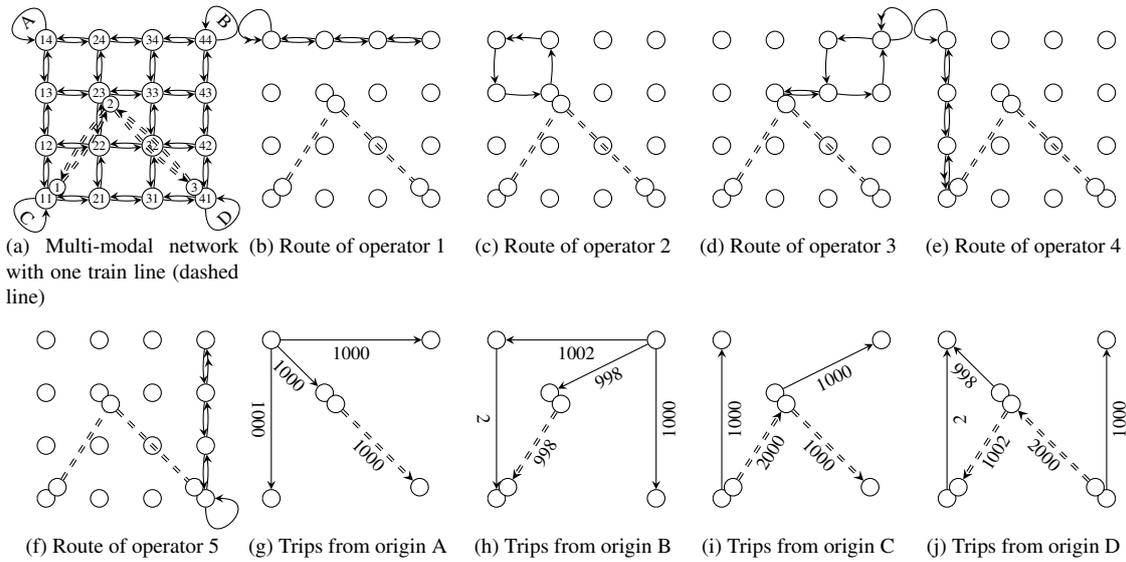


Fig. 1: Resulting routes and flows of scenario 1min - Double arrows indicate termini

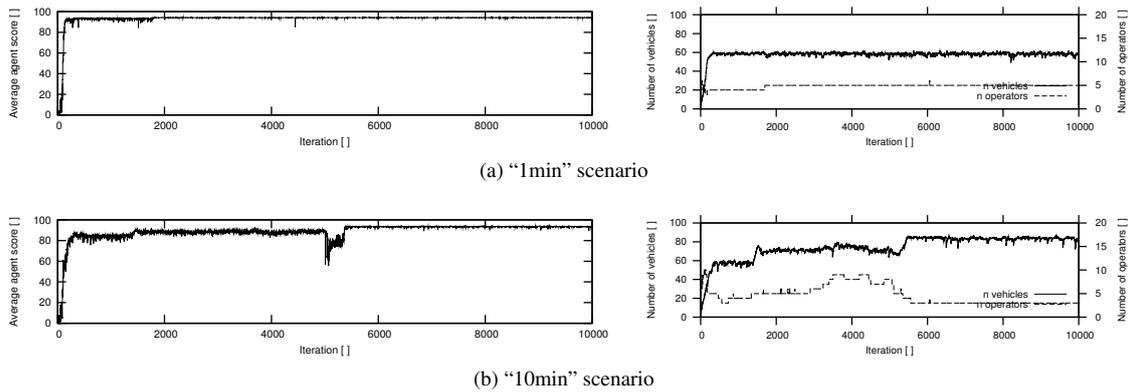


Fig. 2: Average score of the passenger agents, the number of operators with profit and the number of their vehicles for each iteration - Scenarios 1min, 10min

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.

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 "1min" scenario, the train departs every minute. Figures 1b to 1f show the routes of the five operators serving any passengers. 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 1g to 1j. Most or all trips of one

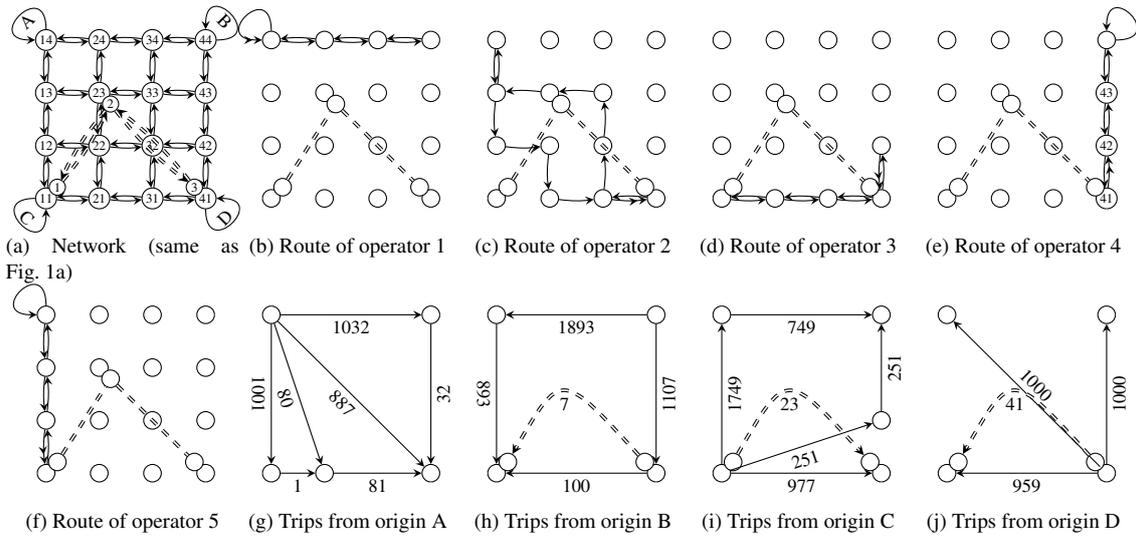


Fig. 3: Resulting routes and flows of scenario 60min - Double arrows indicate termini

relation use the same route.

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 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 2a.

In the “60min” scenario, the train departs every hour. Figure 3 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 now uses minibus services. 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 the link from 41 to 42, see Figure 3e. In this case, it seems that the system is stuck with a sub-optimal solution, since operator 4 cannot move the terminus, while market entry for a direct competitor would be different. Future versions of the adaptation process will include the option to move the terminus.

What happens if an operator with a superior route enters the market can be seen in Figure 2b. First, the 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.

Figure 4 shows some figures for a systematic variation of the train frequency. 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. One can observe a clear cross-over from a high train frequency regime, where lots of trips use the train, to a low train frequency regime, where all travel is served by minibuses. That cross-over is not continuous, as one might expect, but rather abrupt.

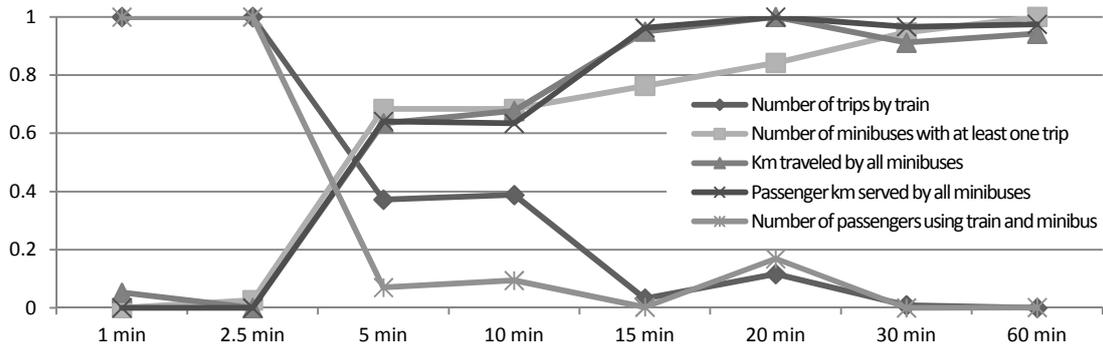


Fig. 4: Key figures for various train frequencies – All values are standardized with 0 being the minimum and 1 being the maximum

4. Conclusion and outlook

This study investigates the application of an evolutionary algorithm to evolve a number of competing paratransit operators when faced with an adaptive demand. It is demonstrated that for illustrative scenarios the approach is able to find plausible solutions, including a plausible sensitivity against frequency changes of a train service. Future studies will investigate additional adaptation options of the operators, but will in particular move to a real world scenario.

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