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ABSTRACT

A genetic algorithm to design efficient large-scale public transport networks is extended. It goes beyond existing approaches by incorporating a dynamic demand response towards both changes in the network and external disruptions. The algorithm is based on an agent-based (MATSim) simulation and tested for the city of Zurich. Compared to the existing public transport system, it proposes a sparser network with substantially higher frequencies. By doing so, the algorithm predicts a higher transit ridership at a lower level of subsidies, thus increasing the effectiveness of public transportation. Moreover, it reliably identifies corridors for potential capacity upgrades. The approach may help transport planners to assess their existing public transport networks and to plan public transport infrastructure for the era of automated vehicles.

INTRODUCTION

Public transport provides connectivity within urban areas across the globe and contributes to social equity by providing basic mobility, accessibility and transport diversity regardless of car ownership, age or income. Other benefits attributable to public transport include less congestion, preservation of open space and the reduction of urban sprawl *(1)*. The challenge in public transport network planning is to find a balance between the interests of both operators (supply) and passengers (demand). While passengers expect direct and frequent door-to-door connections across a city and throughout the day, operators aim to maximize profit and therefore prefer to concentrate on trunk lines during high-demand periods *(2, 3)*. Thus, the planning process can be seen as an optimization problem with two objective functions focusing on maximizing both passenger and operator benefit. However, the process is often constrained by political authorities, who require a minimum level of service and pay out substantial subsidies in return *(4)*.

Historically, most of the public transport networks have evolved over time based on planners' past experience, simple guidelines or demands from local communities *(5)*. Gradually, new routes were added or removed and frequencies were adapted following simple heuristics. Research on more efficient solutions for the complex problem of planning and evaluating public transport networks is still ongoing *(6)*. Despite the substantial progress made in this field, most algorithms presented to this date rely on a static demand for public transportation. By doing so, they neglect the substantial demand impacts caused by changes in the supply *(7)* and cannot be used to predict public transport networks in changing environments e.g. induced by mobility-as-a-service (MaaS) schemes *(8)* or by policy interventions such as substantial congestion charges. This research addresses such limitations by proposing an agent-based evolutionary approach to generate efficient public transport networks based on service-responsive demand. The approach is tested for the city of Zurich.

The paper is structured as follows: First a brief review of state-of-the-art practices in the field of public transport network planning is provided. Then, the simulation framework is introduced and the case study for the city of Zurich, Switzerland is described. Finally, the results are presented and discussed.

BACKGROUND

According to Ceder and Wilson *(9)* the planning process of public transport networks consists of five main levels: *network design*, *frequency setting*, *timetable development*, *bus scheduling* and *driver scheduling*. Each of these planning activities is an NP-hard problem, leading to a great variety of approaches in the literature. There are a number of comprehensive literature reviews which provide an overview across the wide field of public transport network planning *(3, 10, 11)*. In the following, a selection of relevant approaches are presented.

The first heuristic approaches for public transport network planning were developed 40 years ago. For example, Sonntag *(12)* starts with a network containing a line for each origin destination pair. Then, from each OD pair, lines are iteratively deleted and recombined, and passengers are reassigned to new lines according to their travel time. The approach yields a network with short average travel times and few transfers. In contrast, Mandl *(13)* addresses the problem with an empty initial route set. In the first step, a feasible set of routes are generated based on the shortest path between a pair of terminals and the highest number of origin destination pairs. Then, heuristics are applied to improve the quality of the generated route set, minimizing the passengers' total travel cost of (including waiting times, travel times as well as transfer penalties). A number of other algorithms followed *(14)*.

The growing computational power has allowed for a variety of new methodologies to solve the public transport network design problem. Mostly, they enhance a heuristic approach using computational methods. For example, Baaj and Mahmassani *(15)* combine *Artificial Intelligence* with heuristic approaches. Their algorithm consists of three stages: First, in the route generation, an initial set of routes is determined based on a demand matrix and user and operator costs. Meanwhile the search space is reduced by implementing designers' knowledge. Thereafter, the network performance is evaluated (with respect to the number of direct trips, total waiting and transfer time) and is optimized using heuristics. Following a different approach, Zhao *(16)* developed a mathematical computation tool with minimal reliance on heuristics. The tool solves the public transport network planning problem in an efficient way by minimizing the number of transfers and total user costs while maximizing service coverage, given a static demand. The method has been successfully applied to a realistic large-scale scenario. Nikolic and Teodorovic *(17)* developed a model for the public transport network design problem which is based on the *Bee Colony Optimization* meta-heuristics. The algorithm maximizes the number of served passengers and at the same time minimizes the passengers' total in-vehicle time as well as the total number of transfers.

Recently, genetic algorithms have been found to be particularly well suited to address the public transport network design problem *(18)*. In the first formulation by Chakroborty *(18)*, bus lines explore the network through random line generation followed by cross-over and mutation operations, while a fitness function evaluates the competitiveness of the lines. The idea of using genetic algorithms for the public transport network design problem was followed by many later studies. A notable extension is the *Memetic Algorithm* proposed by Zhao et al. *(19)*. Here, four types of operations, 2-opt move (Type A), 2-opt move (Type B), swap move and relocation move, are applied to bus lines to improve their fitness score. The algorithm efficiently minimizes the overall objective function. Another example of the application of genetic algorithms is Rahman et al. *(20)*, who propose a hybridization of two meta-heuristic techniques to solve the public transport network design problem. The approach uses the exploratory feature of the *Guided Local Search* in combination with the *Genetic Algorithm with Elitism*.

Although meta-heuristic, and especially genetic algorithms, are found to fit the public transport network design problem in many studies, most of these studies rely on the assumption of a static demand, which represents a major limitation. In reality, passenger flows depend on the network design *(7)* and should be evaluated in an iterative process to allow for interaction between passenger flows (including mode choice) and the network design. In addition, most studies are based on predefined stop locations, which limits the choice set of the bus operators. In combination with a static demand, this very likely yields biased solutions.

Recent research by Neumann *(2)* opens up a way to address these limitations. He has developed a co-evolutionary algorithm which is inspired by market-oriented and moreover self-organizing public transport systems. Examples of such systems are paratransit systems *(21)*, which are common in developing countries, where they fill gaps left by formal public transport, i.e. by serving low income neighborhoods *(22)*. Unlike formal public transport services, paratransit is mainly unsubsidized and relies on collected fares only. In the algorithm (as in reality) paratransit operators compete with each other trying to reduce their own cost whilst attracting as many passengers as possible. To do so, operators apply genetic procedures such as mutation and selection to their lines *(2)*. This way, a bus network evolves which contains the most profitable lines while the unprofitable lines are gradually dropped. In the model, passengers are able to react to each mutation and to choose their routes accordingly; however, the total demand for public transportation is still assumed to be static given that no mode choice effects are considered. This work substantially extends the approach *(2)* to model large-scale formal public transportation networks including effects the of dynamic demand.

SIMULATION FRAMEWORK

Public transport is in steady competition with other modes such as car, bike and more recent innovations like car-sharing. Improvements or deteriorations in the service of any of the available modes prompt changes to the travel demand of all other modes. Hence, modeling public transport network design with a dynamic demand response requires a simultaneous modeling of other modes to account for their interactions. Thereby, the fine-grained structure of upcoming services such as MaaS schemes requires a representation of travel behaviour on the level of individual persons. The multi-agent transport simulation MATSim *(23)* fulfills these conditions and is therefore used in this research. MATSim contains an elaborate behavioral model on the trip planning side, yet it also allows the simulation of large-scale scenarios within a reasonable computation time due to a queue-based traffic flow representation *(23)*.

In MATSim, each traveler is modeled as an individual agent with individual attributes (e.g. gender, age, income or car availability). An agent is part of a synthetic population, which represents the actual population of a city or region. Each agent acts according to a predefined plan which contains a chain of activities they are supposed to perform. Travel demand arises in the form of relocations required between any two activities. The performance of each agent is evaluated using a utility function, which as a general rule rewards performing an activity and penalizes travel or late arrivals. Following a co-evolutionary algorithm, a stochastic user equilibrium is reached by iteratively modifying the agents' plans until the overall utility of the population stabilizes. Agents' choice dimensions typically are: departure time, route, mode of transport and location of secondary activities (leisure, shopping etc.).

The software allows a detailed modeling of public transport *(24)*. Different vehicle types can be defined. They run along transit line routes according to a schedule with fixed capacities, picking up and dropping off passengers at stop locations. Public transport vehicles are part of the mobility simulation, and as such, they are physically routed through the network, hence they may be delayed by congestion just as cars are. However, the simulation does not consider bus and driver scheduling. Instead, vehicles and drivers are created at the beginning of a line and are removed from the simulation after the final stop of the line.

PUBLIC TRANSPORT NETWORK DESIGN IN MATSIM

A first approach to model public transport network design in MATSim was presented by Neumann *(2)*. Inspired by (for-profit) paratransit systems in developing countries, the model uses a co-evolutionary algorithm. Bus operators are scored according to a fitness function (profit) and can improve their score by mutating their route (expanding it, reducing the number of stops, changing the service hours). After each iteration, the operators adjust the number of vehicles on their routes and announce their updated schedules, routes and the number of departures as well as the headway allowing the passengers to react to the newly introduced schedule when replanning their trips.

The algorithm is similar to a Stackelberg game *(25)* with operators as the leading players introducing their network supply. The passengers as the following players respond according to the least generalized cost path. Passengers will not choose a given travel option anymore if it scores badly. Operators, in turn, can then adjust their network capacity knowing how many passengers have taken a certain route. Although the operators do not cooperate, they have perfect information about the passengers' behavior. In contrast, passengers may have incomplete information due to the changing public transport network. To avoid getting stuck in local optima, agents therefore have to be forced to reroute their trips regularly.

To reduce complexity, the algorithm relies on the following simplifications: Every operator manages only one bus line of the network, that may consist of multiple (overlapping) routes, which can be restricted to a certain service area. At the end of each iteration in the simulation, operators running at a surplus use all of their cash to buy new vehicles, while unprofitable operators sell vehicles to balance their budget. Moreover, operators can move vehicles from low-performing routes to high-performing routes at this stage. Operators with negative equity (after a certain grace period) are removed from the market. Despite the above assumptions, it can be expected that the algorithm in general provides a working public transport network.

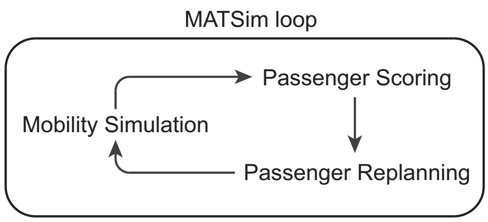
The algorithm by Neumann *(2)* has already been applied to real-world case studies to model both paratransit and formal transit networks *(26, 27)*. However, especially for the case of formal transit networks, the approach still comes with substantial limitations decreasing its applicability to large-scale networks. For example, it relies on a fixed set of bus stops and does not allow mode choice among agents (i.e. it assumes static demand), which biases the resulting network to the default. Moreover, only one vehicle type (minibuses only) is considered.

In this research, the work of Neumann *(2)* is extended to address the above limitations and to allow a more realistic modeling of formal public transport networks including a dynamic demand response.

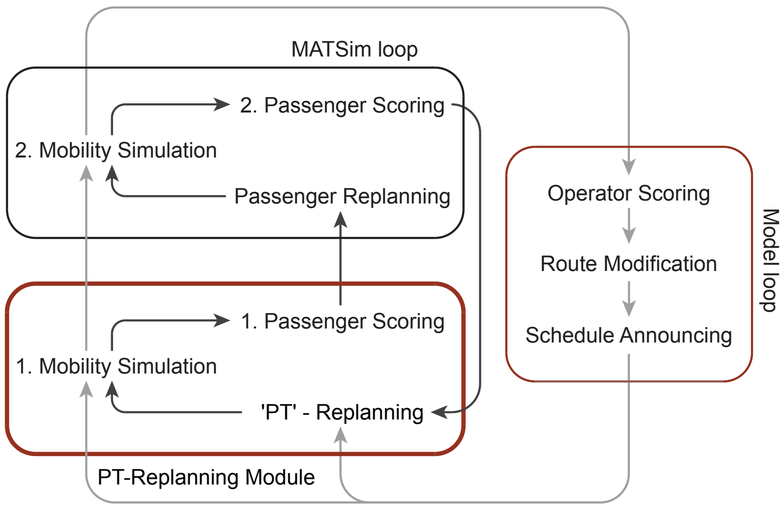
Public transport replanning module

The first innovation aims at including dynamic demand in the model. To avoid local optima and ensure realistic results, this requires that the demand side (passengers) has (close to) complete information on the supply before taking a decision on its response. Hence, an approach was chosen, in which this global equillibrium state is approximated iteratively. As shown earlier, prices (or here: travel times) need to alter much more slowly than consumption in order to yield equilibrated markets *(28)*. Therefore, a *PT-Replanning Module* (Figure 1(b)) is introduced, which artificially increases the demand elasticity.

The module is applied to a decreasing share of agents (from 60% in iteration 1 down to 20% in iteration 200), who - if selected - take their worst performing day plan and reroute all trips in this plan using public transport. This plan then gets scored and marked as prefered. After that, all plans are executed and scored in a mobility simulation step. In the ordinary replanning step, agents can then actually choose a plan. The *PT-Replanning Module* ensures that during the second mobility simulation, agents can take more informed decisions on their travel behavior and provides operators with a valid demand response towards their actions. This is particularly important in the early iterations, when the public transport network is still sparse. In the later iterations, an exaggerated demand response may prevent operators from finding optimal routes and schedules.



(a) Standard MATSim loop *(23)*



(b) MATSim loop including the minibus contribution *(29)* and *PT-Replanning Module*

FIGURE 1 The MATSim Loop

Modification strategies

In each iteration, operators are allowed to modify their routes (cf. Figure 1(b)). In every instance, they choose one of the following modification strategies: *time of operation*, *served stops* and *vehicle type*. Technically, application of the first two strategies creates a new (additional) route, which is operated by one vehicle. Depending on the economic performance of the route, the operator will shift more vehicles to this route in later iterations. Conversely, in the *vehicle type* strategy, the whole fleet operating on a given route is changed to the new vehicle type. A detailed description of the original strategies is given in *(2)*. In this research, the modification strategies were revised and extended to allow for a higher behavioural realism and to make the model applicable for large-scale formal public transport operations.

Operating hours

There is a time extension (at the beginning or at the end) and a time reduction strategy. The decision on how long the period should be extended is based on a random draw with the support of a time provider. The time provider *(2)* supplies the operators with information about high-demand time slots. The time reduction is based on the knowledge of the operator, who is always aware of how many passengers were traveling in its network during each time slot in the previous iteration. The strategies were taken from *(2)* without major modifications.

Served stops

An operator may also extend or reduce the set of stops served by a route. When reducing the number of stops, the operator drops those stops for which the number of boarding and alighting passengers have fallen below a given threshold in the previous iteration (In future applications, this indicator may be replaced by the profit generated by passengers boarding at a stop.). For route extension, the operator can either extend the route at its end or within a given corridor. The stop provider *(2)* assists the operator in finding an appropriate stop within this area by supplying them with information on the demand pattern. In contrast to earlier versions of the algorithm, this research does not rely on a fixed set of stops. Instead, any node in the road network is considered a possible stop location. To still ensure reasonable solutions, a minimal buffer around existing stops and a maximal desired search distance are defined to constrain the set of potential stop locations.

Vehicle type

A vehicle type strategy is added here. It allows operators to tailor the capacity to the respective demand levels. A set of vehicle types is created with defined seat capacities and operating costs. At the beginning of the vehicle type decision process, the strategy manager randomly suggests a new vehicle type for the given route. The decision on the vehicle type is based on the expected profit, which is estimated in the following manner:

1. The maximum number vehicles of the new type is calculated such that the new operating cost do not exceed the existing operating cost.
2. The marginal occupancy is determined, i.e. the occupancy required for the new vehicle type to increase profit.
3. The demand reaction towards the new frequency is estimated based on earlier results (A set of fixed bus lines was simulated with varying frequencies to obtain a functional relation between frequency and demand for the Sioux Falls scenario *(30)*.). From this the expected occupancy of the vehicles is derived.

The higher the difference between expected and marginal occupancy, the more likely the operator is to choose the new vehicle type. In this case, the whole fleet on the given route will be replaced by the new vehicle type.

Subsidies

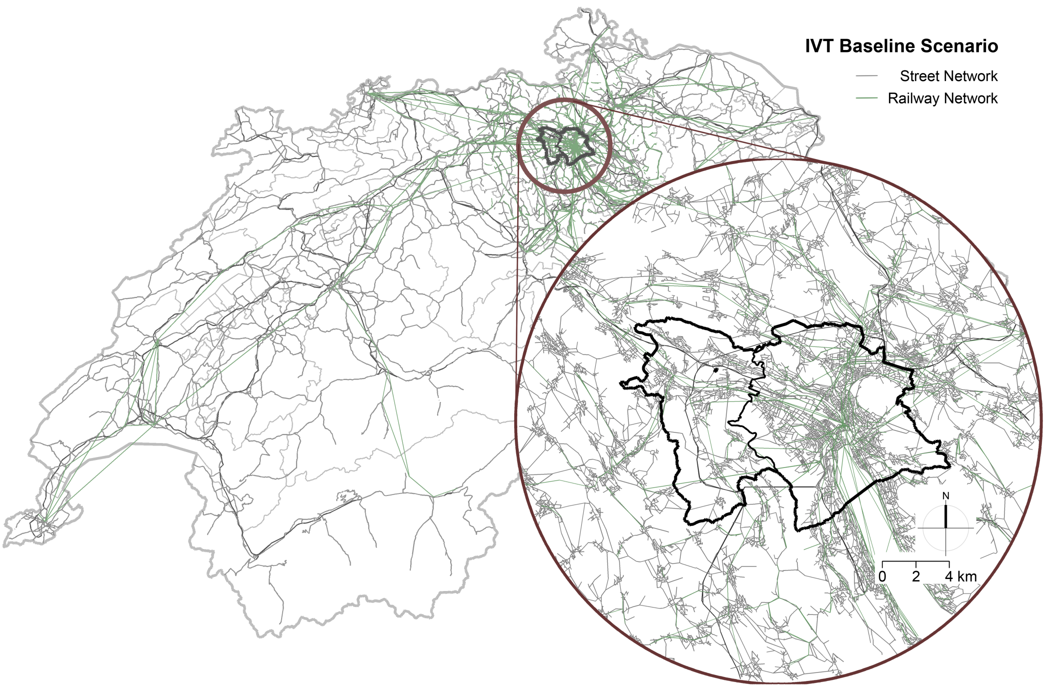
In contrast to paratransit systems, many formal public transport networks are designed not only from a purely economic perspective, but they are also a means to provide basic mobility throughout a region and throughout a day, including low-demand areas and times. To this end, a new feature was added to the simulation, which provides the option to subsidize operators if their network covers a pre-defined list of stops or areas. The subsidies are paid per passenger boarding at one of these stops and are added to the score of the respective route. In this research, all nodes, which after a certain iteration are located in a 500 m × 500 m cell, which is not connected by any bus line, are assumed eligible for subsidies.

SCENARIO AND SETUP

Scenario overview

The model is tested for Zurich, Switzerland. With about 400'000 inhabitants (as of 2016), it is the largest city in Switzerland. Zurich presents an interesting test case, because it has a relatively high public transport mode share of 34%. For this research, the MATSim scenario for Switzerland is used *(31)*. It includes a highly detailed road and public transport network *(32)* and synthetic population as well as cross-border and freight traffic.

To reduce computational complexity, the simulations are conducted for a cutout of the national scenario containing the city of Zurich as well as Dietikon, a district directly adjacent to the city. Figure 2 provides a map of the study area. Note that this cutting process does not affect the street or the railway network. The trains will run as before, all over the railway network of Switzerland, and the agents are able to use every road shown in Figure 2. In the scenario, the eastern part (Zurich) represents a high-density, urban area, whereas the western part (Dietikon) shows a lower density and stands for a typical agglomeration and a more peripheral region. Since this scenario is only a fraction of the main scenario, the number of agents can be reduced substantially. That is, only those agents who perform activities in or cross through the scenario and a two kilometer buffer around it will be considered in the simulation. To further reduce computational burden, the scenario is scaled down to 10 % of the population, i.e. to a total of about 120'000 agents *(31)*. To reduce discretization effects, the capacity of public transport vehicles was scaled down by a factor 6.67 only.



Source: *(31)*; Shape files provided Swisstopo

FIGURE 2 The IVT Baseline Scenario

The public transport network in Zurich consists of buses (diesel and trolley), trams and trains. Due to their infrastructure-dependence, trains are not part of this research and will therefore not be altered. Agents are able to use the trains as before, within and outside of the service area. The existing public transport network will be refered to as *Reference Case*. To test the algorithms, an empty network is generated. To that end, all tram lines as well as most of the bus lines are removed from the scenario. However, some bus lines leading out of the service area are kept in the scenario to minimize border effects.

MATSim setup

All simulation runs are conducted with 600 iterations. The agents are able to freely choose between all transport modes available in the Zurich scenario (cars, public transport, bikes and walk). Each agent stores five daily plans in its choice set. During the replanning step, they will select an existing plan with a 70 % probability. Each of the modifications (rerouting, change mode, change departure time) has a 10 % probability. These values have been found to allow convergence of the MATSim algorithm in earlier studies *(23)*. The parameters for the scoring function are taken from recent studies in the Swiss context *(33)*. All simulations were conducted using the state of the MATSim code and of the Minibus contribution *(29)* as of March 2nd, 2017.

Model setup

At the start, 25 bus operators offer their service each with one route and 5 vehicles. New operators launch a service whenever the number of operators falls below 25 or the share of profitable operators exceeds 90 %. Initial and new operators have a grace period of five iterations before they have to hold positive equity. All routes of a line are required to overlap to prevent operators from offering routes in unconnected areas. The operators have three different vehicle types at their disposal, namely minibuses, standard-buses and articulated-buses. No more new operators will enter the market after 370 iterations, and the modification of the routes is no longer allowed after 420 iterations. However, operators are still allowed to buy and sell vehicles as well as move vehicles from less profitable to more profitable routes until the end of the simulation.

After each MATSim iteration, operators can modify their routes. Modification strategies are assigned randomly with the following probabilities:

- 40 % change of operating hours,
- 7.5 % extend route at one end (within 100 - 1'500 m buffer),
- 7.5 % sideways extension of a route (within 100 - 1'500 m buffer),
- 25 % reduce set of stops served,
- 20 % choose new vehicle type.

In the simulation, passengers pay a distance-based fare of 0.55 CHF/km, which is directly credited towards the operator's score (taxes and fees are neglected). Following Bösch et al. *(34)*, the operating costs consist of a fixed cost of 400 CHF per vehicle per day and a variable component depending on the operating hours, vehicle kilometers and vehicle type:

- *Minibus*: costs of 2.25 CHF/km and 45 CHF/h, capacity: 20 pax
- *Standard bus*: costs of 3.00 CHF/km and 60 CHF/h, capacity: 60 pax
- *Articulated bus*: costs of 3.75 CHF/km and 75 CHF/h, capacity: 100 pax

At the end of an iteration, operators use all remaining cash to buy additional vehicles and assign them to their routes based on the profit generated in the previous iteration. In case of a loss in the previous iteration, buses from the worst-performing routes are sold.

RESULTS

The algorithm has been tested for the city of Zurich to evaluate its ability to solve a realistic public transport network design problem. Two scenarios are analysed: one scenario without any subsidies and one scenario with subsidies paid out in otherwise unprofitable areas. In the scenario with subsidies, eligible stops are first defined after 100 iterations. In the following iterations, all passenger boardings at these stops incur a subsidy of 5 CHF each. The subsidy is increased to 10 CHF for all those areas, which are still unconnected after 150 iterations.

For each scenario, ten simulation runs have been conducted, with different random seeds for the algorithm. The runtime was 40 h per simulation run on three cores of the ETH cluster computer Euler (`https://scicomp.ethz.ch/wiki/Euler`).

Network evolution

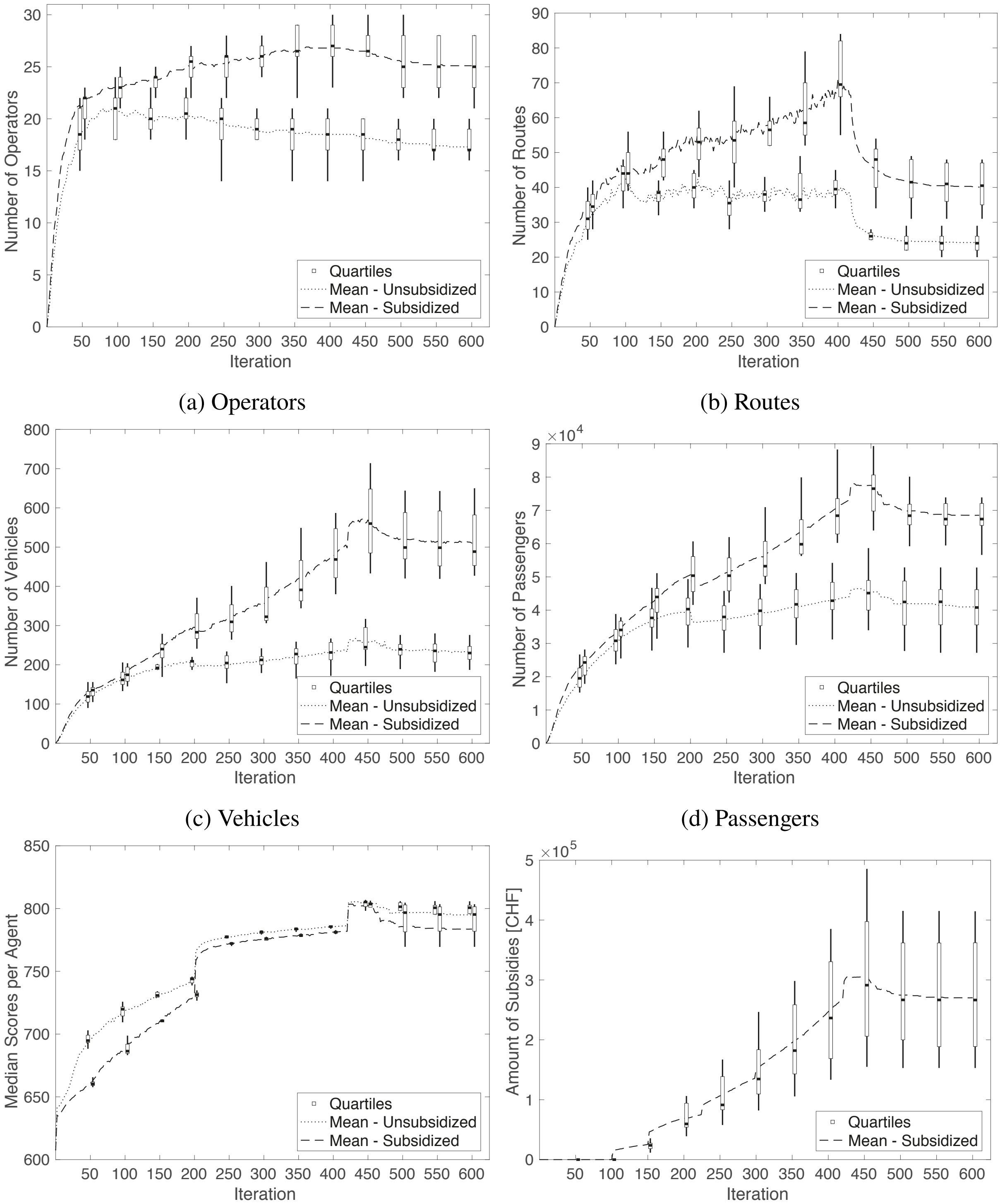
Genetic algorithms usually do not produce optimal, but plausible solutions, provided that an equillibrium state is reached. Figure 3 presents the most important performance indicators for the two scenarios as well as the variation for 10 simulation runs each using different random seeds. In general, all graphs follow a saturation curve with a sharp increase in the beginning and levelling off at later iterations. Deviations from this behaviour occur at iteration 100, when the subsidies set in, at iteration 200, when the *PT-Replanning Module* is turned off and at iteration 420, when operators stop route modifications (excluding changes in the number of vehicles) and passengers stop replanning (i.e. both stick to the available routes and (up to) five day plans).

Figure 3(d) confirms that the *PT-Replanning Module* causes slight bias in the actual demand for public transportation; however, it seems to help generate suitable routes as no effect can be observed in Figure 3(b) at iteration 200. A much stronger discontinuity appears when the replanning modules for both operators and passengers are turned off. After that, the number of routes drops to almost half. In this consolidation process, the number of vehicles and agent scores only slightly decrease. Hence, a more efficient equillibrium state is reached.

Additionally, there are substantial differences between the approach with and the one without subsidies. In the approach with subsidies, the number of operators, routes, vehicles and passengers are almost twice as high. Figure 3(f) indicates a high variation in the subsidies paid in the different scenario runs. All of the simulation runs show a linear increase in subsidies, which only level off at later iterations, when replanning is disabled. The fact that the subsidies grow linearly until iteration 420 may indicate that in later iterations, operators concentrate their growth on subsidized routes. Yet, despite the subsidies, the median score of the agents is not significantly different from the unsubsidized case. However, significant improvements may occur if individual VoTs were considered in this model.

Network features

Table 1 compares the features of the two model networks with the current public transport network in the area (reference case). As can be seen from the table, the algorithm suggests a substantially shorter network with a smaller number of stops. This concentration is in line with Hotelling's theory *(35)*, stating that free competition yields median locations. As a result, passengers are provided shorter wait times at the expense of longer access walk. Also the in-vehicle time is longer, which is a result of operators trying to serve as many profit-generating passengers



(a) Operators

(b) Routes

(c) Vehicles

(d) Passengers

(e) Agent scores

(f) Subsidies

FIGURE 3 Evolution of the several performance indicators of the model averaged over all runs.

as possible rather than providing the shortest path for each OD-pair. Nevertheless, there are substantial differences between the scenarios with and without subsidies: In the scenario with subsidies, the network is 30 % longer and serves 70 % more passengers resulting in 55 % more trips. While the network is still considerably shorter than in the reference case, the subsidized model network produces more vehicle kilometers and serves substantially more passengers at a 15 % lower level of subsidies.

TABLE 1 Network statistics (averaged over 10 simulation runs)

	Reference Case	**Algorithm** without subsidies	with subsidies
Operator Perspective			
Network length [km]:	463	217	290
Number of stops:	1 270	701	896
Avg. frequency peak hour[a]:	4.7	6.7	9.0
Veh. time driven [h]:	5 862	2 630	5 698
Veh. km driven [km]:	92 411	45 700	101 989
Passengers [pax]:	51 161	40 992	68 520
Pax. km traveled [km]:	124 011	163 335	243 092
Subsidies [CHF]:	323 438[b]	0	270 159
Customer Perspective			
Observed trips:	22 948	19 087	29 700
Avg. trip time [min]:	28.9	37.5	37.8
Avg. in-vehicle time [min]:	12.8	17.5	16.1
Median access walk distance [m]:	296	372	388
Median egress walk distance [m]:	271	346	369
Avg. waiting time at first stop [min]:	3.7	3.1	2.4
Avg. waiting time at transfers [min]:	4.0	3.8	3.8
Avg. number of transfers:	0.45	0.34	0.46

[a] Average number of departures per hour between 7.30/8.00 am and 5.30/6.00 pm per line.
[b] estimated based on the veh. km driven, average operating cost of 7.14 CHF/km for city buses *(34)* and subsidies of 50% of the operating costs *(4)*

Spatial coverage

However, a comparison between the two networks would be incomplete without considering the spatial and the temporal dimensions. To this end, Figure 5 presents the network graphs of the public transport networks. In terms of capacity, the figure shows considerable differences between the unsubsidized model and the reference case. While the capacity provided by the algorithm without subsidies appears to be lower and more tailored to the main passenger flows, the reference case provides higher capacities both in the city center and towards the outskirts (in particular along the lake and towards the north). The algorithm with subsidies proposes a high level of capacities similar to the reference case. Interestingly, it also assigns particularly high capacities towards the western suburbs, to the Hardbrücke as well as to the north of the city of Zurich. In all three of these areas, larger upgrades in the public transport network are currently planned by the city of Zurich.

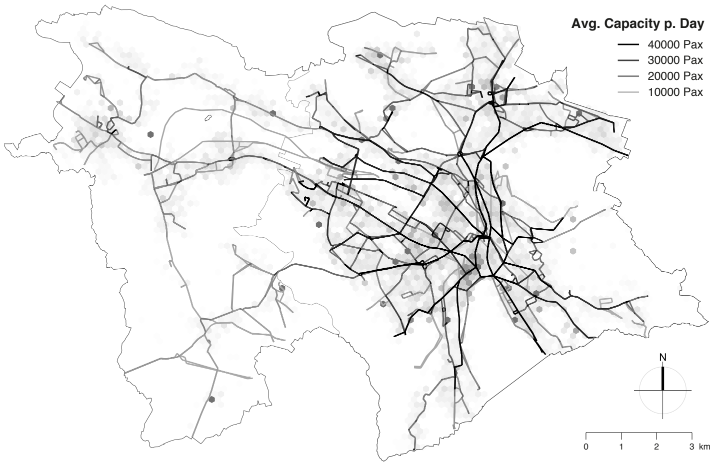
Following Hotelling's theory *(35)*, the unsubsidized network created by the algorithm is less dense than the reference case, and also shows a stronger hierarchy with only few main lines and many lines running at lower capacities (or only occuring in some of the ten simulation runs). Moreover, it only covers the city center and its connections to the northern boroughs. In contrast, the reference network and the subsidized model network cover the whole city of Zurich and the major activity locations in the district of Dietikon.

According to the literature *(36)*, the attractiveness of public transport (and thus, its overall mode share) strongly depends on the availability of stops within walking distance of trip origins and destinations. Hence, a formal public transport operator aims at a high density of bus stops throughout the service area. A suitable indicator is the catchment area, here defined by a 500 m buffer around bus stops. While in the reference case 99 % of all households are located within this catchment area, this number is slightly lower for the model networks (88 % with subsidies, 80 % without subsidies). Hence, despite the different network structure, also the networks generated by the algorithm appear to provide a relatively high level of accessibility for the area.

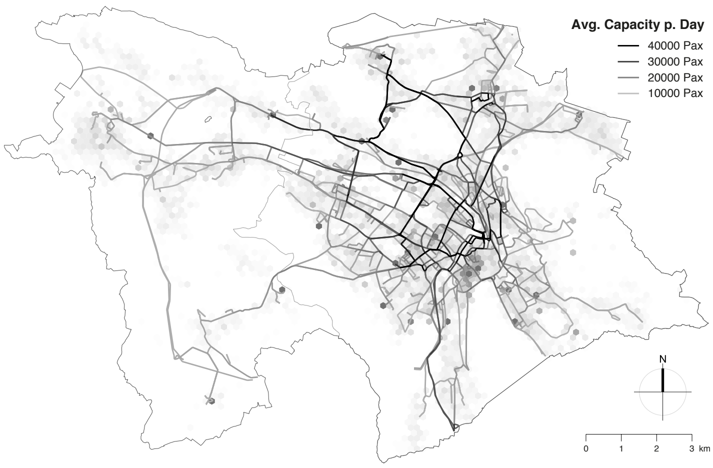
Service hours

For the temporal dimension, a comparison of the number of agents en route with public transportaion for the different cases is presented in Figure 5(a). Throughout the day, the subsidited model network shows the highest load of travellers. Also the unsubsidized has a higher passenger load than the reference case, despite the total number of travellers being lower. This is a result of the considerably higher in-vehicle times in the model networks (cf. Table 1). In addition, the model networks only show peaks in demand around noon and in the afternoon, but not in the morning. Instead their load is stable throughout the morning, which may indicate that the systems (also) attracts different user groups than the formal public transport scheme, which currently is in place.

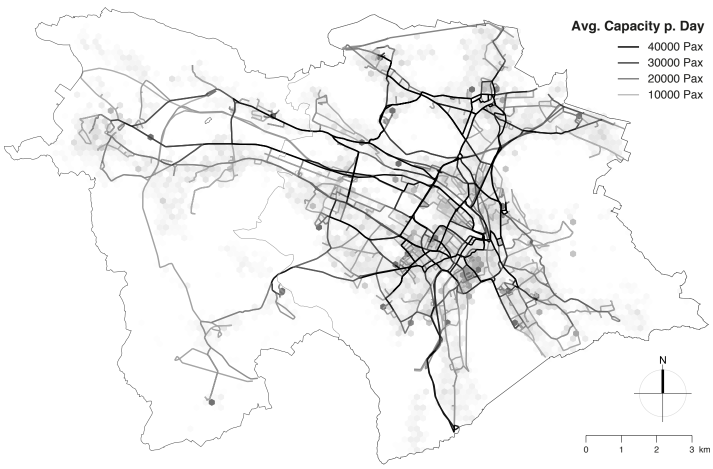
Figure 5(b) confirmes earlier results, in that the model networks show higher average frequencies troughout the day. Especially in the morning, when the number of travellers en route is similar between the three cases, the frequencies in the model networks are substantially higher than in the reference case. This again indicates that a similar level of service is reached through higher frequencies on fewer different bus lines.



(a) Reference Case

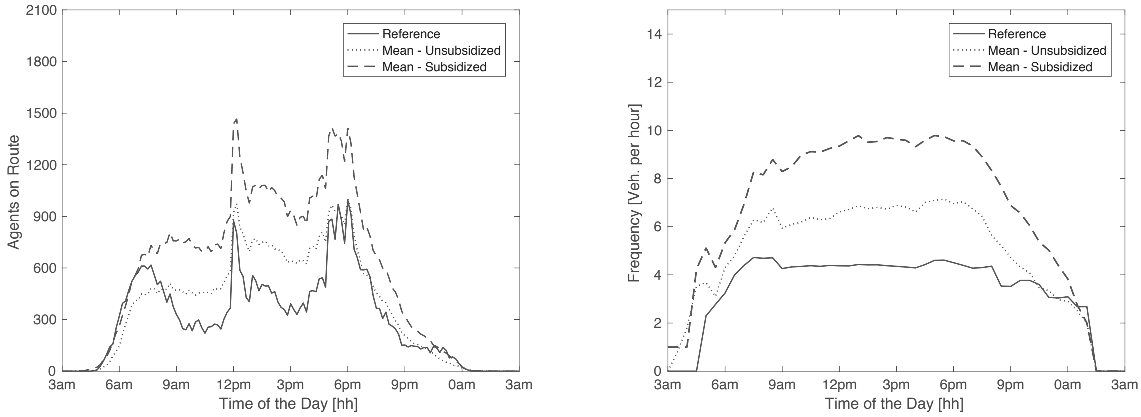


(b) Model without subsidies - averaged over all simulation runs



(c) Model with subsidies - averaged over all simulation runs

FIGURE 4 Capacity map (background: activity density)



(a) Passengers travelling with public transportation (b) Frequencies

FIGURE 5 Temporal distribution of averaged frequencies and travellers

DISCUSSION

As shown above, the algorithm presented in this research addresses the public transport network design problem on the city-level and with a dynamic demand response. This is achieved by extending MATSim algorithms for paratransit network design *(2)* to incorporate dynamic demand, different vehicle types and subsidies. The approach overcomes limitations of earlier approaches, which mostly rely on static demand assumptions or only covered subnetworks *(14, 16, 18, 27)*. Nevertheless, some aspects still have to be considered when interpreting the results.

In contrast to formal public transport networks, which are planned to provide maximal accessibility levels and to follow various political constraints, the main objective in the algorithm is profit. While political constraints can be incorporated using subsidies (or penalties), the algorithm focuses on efficient operations, which likely yields public transport networks different from the ones currently in existence. Moreover, it has to be noted that in the algorithms, operators are only active in single corridors and therefore do not perform optimizations from a global perspective such as minimizing transfer times or using certain less profitable lines as feeders for other lines. The algorithm (as other genetic algorithms, too) does not provide globally optimal solutions. However, the limitations are weak enough to still allow plausible, locally optimal solutions.

It is important to understand that given the high level of randomness in the approach, there is significant variation in the networks generated by the algorithm. Therefore, multiple simulation runs using different random seeds need to be conducted. For posterior analyses as well as policy recommendations, a set of different simulation runs has to be combined. One way to reduce this randomness would be to define heuristics in the route modification step; though this may result in biased and thus less optimal solutions.

Compared to the existing public transport network, the algorithm generates sparser networks, on which vehicles run at very high frequencies. Such a behaviour is in line with the more recent literature indicating that high frequencies are valued higher than shorter access times or even a low number of transfers *(7, 37)*. In the case of unsubsidized operations, the algorithm suggests a network, which is limited to the central areas as well as major demand corridors. Similar to the reference network, the subsidized network generated by the algorithm also covers areas of lower demand. Thus, it can be assumed that despite minor differences in the network graphs, the algorithms provide plausible and efficient solutions to the network design problem. As an immediate result, the case study shows that public transport operations in the city of Zurich could be conducted with substantially lower subsidies, while maintaining a similar level of accessibility and even increasing ridership.

What makes the approach particularly interesting is that it can not only be used to assess the efficiency of current public transport operations or to identify corridors deserving an expansion in capacity (for all places where the algorithm proposes a higher capacity than the reference case, capacity upgrades are in progress). Because the approach does not rely on a static demand, it can be used as a planning tool to design public transport networks for changing environments, i.e. in lieu of a congestion charge or for a world of automated vehicles, where cost structures of both buses and taxis will change substantially *(34)*.

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