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SIMULATION-BASED REPLACEMENT LINE AND HEADWAY OPTIMIZATION

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ABSTRACT

We present a study on simulation-based replacement line and headway optimization for the Viennese public transportation system. The discussed problem focuses on scheduled closures of subway lines. A genetic algorithm is proposed to design replacement lines and potentially adjust the headways of all lines in the network. Candidate networks are simulated to evaluate their solution quality. The underlying discrete event simulation model has several stochastic elements (e.g., vehicle travel and turning maneuver times). Passenger creation is a Poisson process which uses daily origin destination matrices based on anonymous mobile phone and count data. Vehicles are subject to capacity restrictions. Computational insights are gained from three real-world based test instance. Our problem-specific genetic algorithm creates not only good but also robust solutions by taking stochastic elements into account.

1 INTRODUCTION

Public transportation networks are important for larger urban areas (Roth et al. 2012), but such infrastructure has to be maintained on a regular basis. Railbound lines (i.e., railway, subway, tramway), require the partial closure of these lines for some tasks, e.g., when tracks or stations need to be renewed. A closure may last for weeks or even months. Since many passengers are typically affected by these events, proper replacement services need to be planned. These replacement services may include the establishment of extra bus lines. However, in particular during peak-hours, the capacity of a bus line might be insufficient to compensate for a (partial) subway shutdown. Moreover, some passengers might change their path due to the changes in the network. Therefore, other measures have to be taken in consideration, including headway adjustments to provide additional capacity on critical segments.

This work deals with the problem of determining routes for replacement services and adjusting headways in case of scheduled closures of subway lines. A simulation optimization approach based on two layers is proposed to solve the problem: A *genetic algorithm* (GA; see Holland 1975) is used to generate candidate solutions, consisting of routes for new bus lines and headways for all lines. The candidate solutions are then evaluated by a *discrete event simulation model* that particularly simulates the passenger flow. The solution quality is then returned and the GA uses any information regarding infeasibilities to adjust the candidate solutions of the next generation. The general idea is to improve the population of candidate solutions over generations. Since subway closures for renewing the infrastructure is usually scheduled well in advance, the computation time is typically not critical.

In the literature, the problem of setting up a transit network by defining the routes and the headways of the lines is typically either called *transit network design (and frequency setting) problem* (TNDFSP) or *line planning problem*. The problem considered in the paper at hand relates to the TNDFSP as routes

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for the replacement lines need to be planned and headways may have to be adjusted. Particularly with respect to the passenger flow sub-problem, the existing lines of the network have to be considered as well. The routes of the existing lines should remain unchanged, though. It is shown by Farahani et al. (2013) that GAs are popular for solving the TNDFSP. The GA layer of the algorithm employed in this paper is based on the GA by Kiefer 2020 and extended by a feedback mechanism to interact with the simulation layer. Moreover, headways are set in a different way.

The concept of combining an optimization method with a passenger simulation model is not new in public transport disruption management. Kroon et al. (2015) combine an optimization model for rolling stock rescheduling and a simulation model for the passenger flow when dealing with service disruptions.

The proposed approach is applied to several real-world test instances based on the Viennese public transportation network and is able to out-perform the results of standard measures. The paper is structured as follows. First, the problem is described in Section 2. Then, in Section 3 the method is presented. The experiment setup is discussed in Section 4 and the computational results are shown in Section 5. Finally, Section 6 concludes and shows some possible future prospects.

2 PROBLEM STATEMENT

The problem described in this section partly focuses on the Viennese public transport network that is later used for the computational tests. However, since most of the characteristics may be found in any urban public transport network, the proposed approach is generally applicable (perhaps with minor modifications).

The Viennese public transportation system consists of about 5,400 stations. Its subway lines have a length of over 79km (49 miles) and its – or other (railbound) means of transportation – infrastructure requires maintenance and/or renewal on a regular basis. The problem discussed in this paper deals with scheduled closures of a subway line in order renew the tracks and the stations. In particular we focus on the recent case of the renewal Vienna's oldest subway line (U4; constructed from 1976 to 1981). For that purpose, large segments of the line are successively closed for several months.

Since many passengers are affected by subway closures, appropriate measures need to be planned to limit the negative effects. These measures include the establishment of replacement services via new bus lines and headway adjustments (within certain bounds) of the existing lines. Headways need to be adapted to account for any changes in the passenger flow due to the disruption. Hence, a bigger capacity, i.e., a shorter headway, needs to be provided on lines where many passenger are expected to travel. On the other hand, vehicles of less popular lines might be retracted. Passengers are assumed to travel along their respective shortest path. Furthermore, passengers are assumed ignore the headways for estimating waiting times. Rather a fixed transfer time is considered when computing the shortest path.

The considered network consists of subway, tram, bus, and train lines. The fleet size is known and used as a constraint. In order to establish replacement services, the bus fleet needs to be larger than usual.

The objective is to minimize the mean travel time of passengers that are directly affected by the disruption. The travel time includes the actual headway-dependent waiting time, the transfer time and the in-vehicle time. The other passengers might be implicitly affected by the established measures. However, any deterioration of their travel times would be limited to extended waiting times. By setting bounds for the headways of the existing lines, one can ensure that the negative effects for these passengers do not exceed a certain level. A passenger-oriented objective function is reasonable in this context, since replacement services are only established for a relatively short period, and hence their effect on costs is less severe. Still, costs can be taken implicitly into account by limiting the extra fleet for the replacement services.

It is assumed that the replacement lines visit the same stations in both directions. In particular, circle lines are prohibited. This assumption reflects the current structure of the lines in Vienna, where only a few lines have short loops, but mainly to perform turns. Moreover, the number of stops along a line is limited and so is the largest distance between adjacent stops.

A network consisting of two lines is illustrated in Figure 1. The nodes include the physical stations of the network, denoted by g_i. The stops of the lines have to be treated as individual nodes (s_i) in order to model the passenger flow. At station g_2 for example, passengers are allowed to transfer from one line to the other. The stops of a line are connected by arcs.

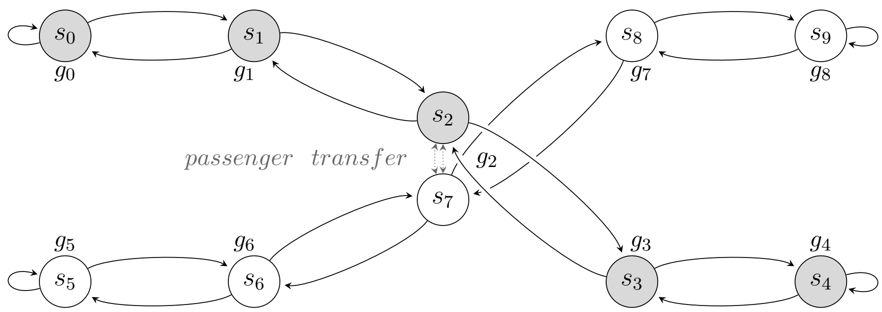


Figure 1: Example of two intersecting lines (directed graph).

3 METHODOLOGY

A public transportation system can be considered as a queuing network with non-exponentially distributed service times and synchronization. It is thereby too complex to merely apply analytic methods from queuing theory like Jackson networks (Jackson 1963) and its extensions. This is why we employ *simulation-based optimization* as introduced by Fu (2002). Its functional principle is as such (Figure 2): an optimizer (e.g., a GA) generates candidate solutions which are handed over to a simulation model for evaluation. The result of this process (i.e., the respective solution quality and feasibility status) is then sent back to the algorithm in order to generate new and better solutions. For a review on the method, the reader is referred to Juan et al. (2015). The next subsections deal with the two aforementioned building blocks of simulation optimization: the GA (Section 3.1) and the simulation model (Section 3.2).

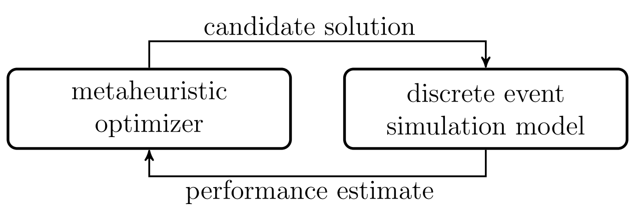


Figure 2: Functional principle of simulation-based optimization (Fu 2002).

3.1 Genetic Algorithm

The implemented GA extends the one by Kiefer (2020). The candidate solutions created by the GA store the information of the routes of the replacement lines and the headways of all lines. Thereby, the whole network is defined, since the routes of the existing lines are fixed. Both, the routes and the headways are stored in vectors. The maximum number of replacement lines is given and therefore the size of the vectors is known. Some of the routes may be empty, though. The solution representation is illustrated in Figure 3 where R_i denotes a route and H_i refers to a headway. The routes themselves are again vectors that contain the sequence of visited stations.

The structure of the GA is sketched in Figure 4. The algorithm first generates an initial population corresponding to a certain number of individuals, i.e., candidate solutions. As long as the time limit is

R_1	R_2	R_3	H_1	H_2	H_3	H_4	H_5	H_6	H_7

Figure 3: Solution representation.

not reached, a new population is created. The best solution of the old population is directly transferred to the new population. Another $\nu - 1$ randomly selected individuals are transferred from the old population. For creating the remaining individuals, parents are first determined by means of tournament selection. A uniform crossover of the two parents is then applied to form the offspring for the new population. The routes and the headways of all but the best solution might be mutated. Afterwards the passenger behaviour is heuristically estimated. If constraints regarding the fleet size or the line capacity are expected to be violated, corrections are performed by adjusting the headways. If the network is connected and both the fleet and the capacity constraints are likely to hold, the candidate network is passed to the simulation. The simulation then returns the solution quality with respect to the travel time and potentially information about occurred fleet or capacity violations. The latter is used to make adjustments for the next generation. All steps are discussed in more detail in the following paragraphs.

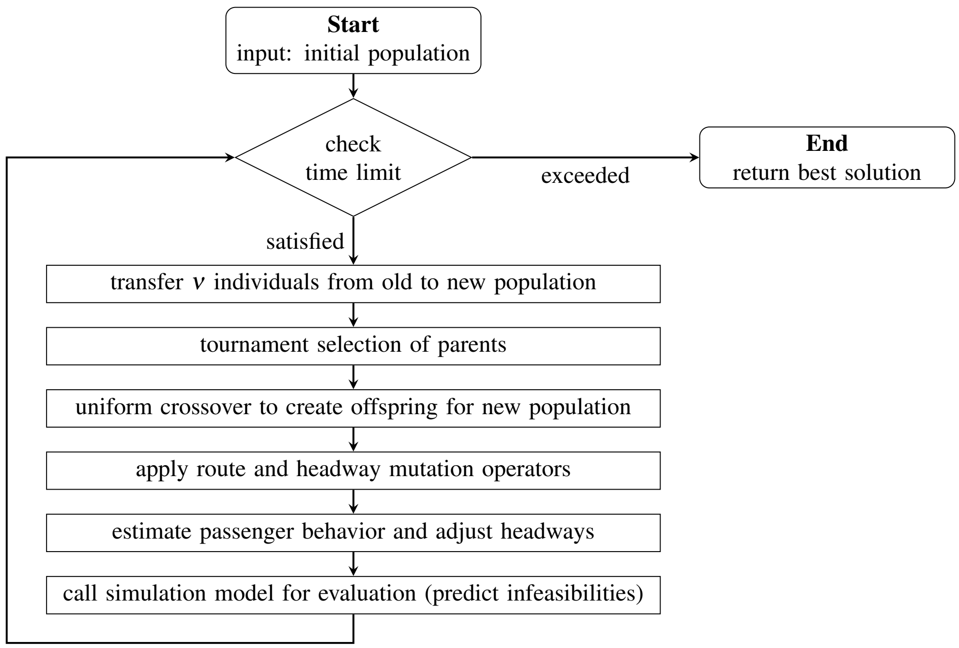


Figure 4: Flow chart of the GA: generation of new populations (based on: Kiefer 2020).

Headways are generally either drawn from a uniform or a truncated normal distribution. Instance parameters specify the minimum and maximum headway. These bounds are always respected, even when they are not mentioned explicitly. The mean of the truncated normal distribution depends on the old solution(s) and a parameter is used as standard deviation. Regarding the route construction, all employed operators ensure that the bus lines may at least be operated with the largest headway and still respect the fleet size constraint. If the fleet requirements exceeded the size, the considered operation would not be performed, e.g., a line would not be extended or no additional line would be created.

Initial Population

The first solution of the initial population consists of replacement line(s) that cover exactly the closed subway segments. The headways of the existing lines are set to their original values and the headways of the replacement lines are set to the shortest possible headway. For the other solutions, a random number (≥ 1) of replacement lines are generated. A new line randomly starts at a disrupted node. The line is then iteratively extended by a random number of stops. The nodes themselves are again randomly selected, where subway nodes have higher probabilities of being picked. The headways of the lines are drawn from a truncated normal distribution. In case of existing lines the original headway is used as mean, and for the new lines the average of the bounds is used.

New Generation

The best solution of the old population is transferred to the new population without any modification. The other individuals, that are transferred are adjusted if they are infeasible. Moreover, their headways are newly drawn from a truncated normal distribution with the old headway as mean.

The remaining individuals of the new generation are created via crossover of two parents. Therefore, the parents are first selected by tournament selection: a certain number of individuals is randomly picked from the old generation and the best with respect to its objective value is chosen as parent. A uniform crossover is applied to form the offspring. For each route index either the route of the first or the second parent is taken for the first offspring. A second offspring is created by choosing exactly the opposite routes. The headways of the replacement lines are drawn from a truncated normal distribution with their respective old headway as mean. The headways of the existing lines are either computed by an average crossover or an alpha-beta crossover Takahashi and Kita 2001. The crossover operator is selected randomly, where the selection probability of each operator is controlled by a parameter.

The average crossover draws the headway from a truncated normal distribution. The (weighted) average of the headways of this line of both parents is used as mean, where the value is biased towards the parent with the better objective value. The alpha-beta crossover uses a uniform distribution instead. Let h_b denote the headway of the considered line of the parent with the better objective value and let h_w denote the headway of the worse parent. The difference of the two headways is denoted by $d = |h_b - h_w|$. If $h_b < h_w$ the headway is drawn from the interval $[h_b - \alpha \cdot d, h_w + \beta \cdot d]$ and $[h_w - \beta \cdot d, h_b + \alpha \cdot d]$ otherwise, where α and β denote parameters.

The crossover is illustrated in Figure 5. In the top line R_i and r_i denote the routes stored in the first and the second parent, respectively. Similarly, H_i and h_i denote the respective headways. The indices 4 to 7 refer to those of the existing lines. The bottom line shows the offspring. The headways of the first and the second offspring are denoted by N_i and n_i, respectively. The first offspring gets the routes R_1, r_2, and R_3 at random. The other routes are therefore used for the second offspring. The headways that correspond to the transferred routes are used to define the distribution where the new headway is drawn from. For example, N_1 is drawn from a truncated normal distribution with mean H_1. The distribution for drawing the headways of the existing lines is affected by the headways with the same index of both parents, e.g., $H4$ and $h4$ are used for $N4$ (and $n4$).

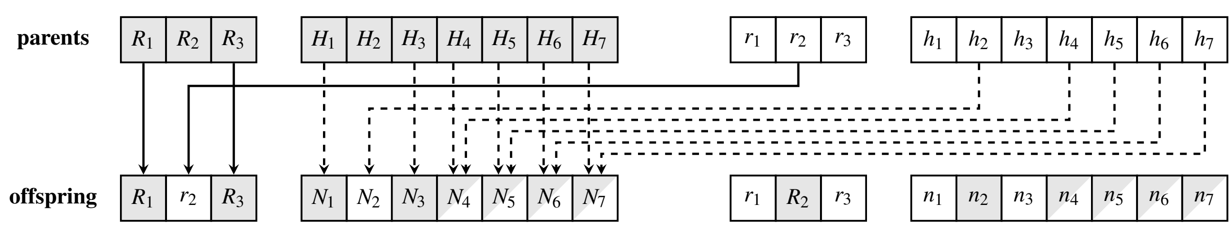


Figure 5: Crossover.

Mutation

All but the best solution might be mutated. The probabilities of mutating the routes and the headways are controlled by separate parameters. If a solution should be mutated with respect to its route structure, one of the following operators is applied once: *add line*, *remove line*, *add node*, *remove node*, *move node*, *swap nodes*. Their selection probabilities correspond to parameters. Depending on the particular solution some operators might be excluded (e.g., no line can be deleted if all of them are already empty).

The *add line* operator creates a new replacement line in the same way as the initial lines are generated. The *remove line* operator removes a random line with a bias towards those with few passengers. *Add node* (*remove node*) adds (removes) a random node from a random route. Finally, *move node* moves a random node to a new position on the same route and *swap nodes* swaps two random nodes of the same route.

The headway of each line may be mutated with a certain probability. In this case a new headway is drawn from a uniform distribution with the minimum and maximum headway as bounds.

Pre-Evaluation and Feedback Mechanism

Before sending candidate solutions to the simulation, they are heuristically pre-evaluated in a deterministic way. For that purpose, the passengers are routed along their shortest paths in the network without any capacity restrictions. Thereby, the capacity requirements of the lines can be estimated. The shortest path is generally generated by Dijkstra's algorithm (Dijkstra 1959). Theoretically, the network might be unconnected. Hence, as soon as a destination cannot be reached from an origin, the candidate solution is known to be infeasible.

Given, that the network is connected, the headways are adjusted before eventually sending the candidate solution to the simulation. This is done by a heuristic that should help to reduce the number of infeasible solutions sent to the simulation and thereby speed up the program. First, each headway is reduced (if necessary) to meet at least the minimum capacity requirements along the line. Afterwards, the headways of the lines are iteratively increased until the fleet size constraint is satisfied. Lines are processed in the order of their passenger volume starting with the most unpopular one. A headway is never increased beyond the level that is needed to satisfy the capacity requirements. If the fleet size constraint of at least one type is probably violated, the solution is marked as infeasible and will not be sent to the simulation.

A candidate solution can generally be infeasible for three reasons: the network is unconnected, the fleet size is exceeded, the capacity of a line is smaller than the demand. The latter refers to the case when passengers cannot embark at a stop due to insufficient capacity.

The routes of the solutions that do not descend from two parents are modified if the network is unconnected or passengers cannot embark, while both violations are treated in the same way. If the node where passengers cannot embark (or the unconnected node) is located along the subway closure, a new line is generated that originates at that node. If the limit for replacement lines is already reached, a line is first deleted at random. The network of the offspring of two parents has changed anyway and therefore remains unchanged.

Infeasiblities regarding the line capacity and the fleet size of an old solution affect the distribution where the headways of the new solution are drawn from. Whenever headways of an old solution are used to define a distribution, either its mean (truncated normal) or its bounds (uniform), these headways are shifted depending on the occurred infeasibility: the headway is increased by ζ if the fleet size of the type is exceeded and decreased by ζ if the line capacity is insufficient, where ζ denotes a parameter.

3.2 Simulation Model

The features of the discrete event simulation model are as such: 1) The creation of passengers is driven by a time-dependent Poisson process. 2) Passenger transfer times and vehicle turning maneuver times are triangular ($\pm 15\%$) distributed. Thus, passenger times (travel time = waiting + in-vehicle + transfer time) are stochastic. 3) The vehicle travel times are direction-dependent (log-normal distribution for subways, triangular ($\pm 15\%$) for all other means of transportation).

More details on the Viennese subway simulation model (including vehicle travel time distribution fitting and model validation) can be found in Schmaranzer et al. (2019a). Due to the lack of raw data on the other means of public transportation (i.e., railway, tramway, bus), certain assumptions (like using aforementioned triangular distribution for vehicle travel times) had to be made.

Each passenger is assigned a path, generated by Dijkstra's shortest path algorithm (Dijkstra 1959). However, whenever a vehicle stops along the path of a passenger and leads to the same geographical location (Figure 1), the passenger boards that particular vehicle.

Because there are several stochastic elements, replications (i.e., simulation re-runs) are required to account for statistical significance. We employ a varying number of replications with a minimum of three and a maximum of 50 replications. The sequential evaluation process terminates once a 99.9% confidence interval with a relative error of 1% on the mean of the objective value (mean travel time per simulated passenger) has been constructed (Schmaranzer et al. 2019b). If a passenger cannot board a vehicle due to overcrowding three times in a row the simulation is terminated, the solution is deemed infeasible, and no (more) replications are performed.

The number of entities (or agents) has a significant impact on the respective simulation model's run time. Due to the large number of samples, the standard deviation in mean travel time per simulated passenger is quite low. This allows for the introduction of a "global denominator". It reduces the number of passengers as well as the vehicle capacity by a factor of three. This step of course increases standard deviation, but reduces the simulation run time significantly.

4 COMPUTATIONAL EXPERIMENT SETUP

The passenger data includes the origin destination (OD) matrix for subway stations and the count data for lines of all other transport types but trains. The OD matrix was created by the MatchMobile project (IKK 2017), using anonymous mobile phone and infrared count data. The trains in Vienna are operated by a different company and their count or other raw data could not be provided.

For the instances only a certain region of the Vienna is considered. The original OD matrix therefore needs to be adjusted. For that purpose the shortest path of all passengers that either start or end their journey in the considered region is evaluated. Since the OD demand refers to subway passengers, only subway lines are used for computing the shortest path and all lines are assumed to be functional. At the node where the passengers enter (leave) the considered region the OD demand from (to) this node is increased accordingly. For example, let A and C denote two subway nodes with a corresponding demand of d_{AC}. Assume that A lies in the considered region and C does not. The last node along the shortest path from A to C that is still in the region is denoted by B. The OD demand from A to B is therefore increased by d_{AC}.

In order to reduce the scale of the simulation model, only subway passengers that are affected by the disruption are simulated. Passengers are assumed to be affected by the disruption if their original shortest path in the undisrupted network cannot be traversed anymore. Subway passengers whose shortest path in the undisturbed network remains unchanged after the closure are assumed to take their original shortest path even if a newly established replacement line offers a shortcut. These passengers are therefore used to reduce the remaining capacity along their shortest paths. The passenger count data of non-subway lines is incorporated by reducing their capacities accordingly. The residual capacity may then be used by the affected passengers.

The U4 subway line is undergoing renovation and modernization since 2016 (Wiener Linien 2020). First, a section in the south-west between Hütteldorf (HD) and Schönbrunn (SB) was closed down during summer 2016. Figure 6a depicts this test instance, which is referred to as *west*. It covers approximately one fifth of the Viennese public transportation network. The number of passengers affected by the disruption per day is 95,000. Because the network is not very dense in the outer regions, passengers do not have many alternative route options.

Next, the *north* instance (Figure 7a), where – similar to the *west* test instance – the end of the line is out of order. The disrupted section is between Heiligenstadt (HS) and Schottenring (SR), the latter being a highly frequented subway crossing station. This test instance covers about one quarter of the Viennese public transportation network. Approximately 110,000 passengers per day are affected by the disruption.

The *center* instance (Figure 8a) covers more than half of the Viennese network and is the largest of our three test instances. It is located south of the city center, hence the name. About 180,000 passengers are affected by the disruption between Längenfeldgasse (LG) and Karlsplatz (KP), both of them being highly frequented subway crossing stations. The disrupted section is known to have a high vehicle occupancy. Table 1 contains the vehicle budget and the affected passenger volume of each test instance.

Table 1: Vehicle budget and affected passenger volume per test instance.

test instance	available vehicles per transportation type				affected pas.
name	subway (U1-4)	subway (U6)	tramway	bus	volume
west	20	8	52	72	95,000
north	28	12	28	32	110,000
center	48	12	48	98	180,000

The GA (Section 3.1) has various parameters that must to be tuned to fit the problem. We defined a set of reasonable values for the parameters and ran full factorial experiments. Five independent optimization runs (not to be confused with replications) were performed. The timeout for each test instance and per optimization run was 60 hours.

All experiments (including the parameter tuning) were conducted on the Vienna Scientific Cluster 3 (VSC 2018), which is a high performance computing cluster comprised of 2,020 nodes, each one equipped with two Intel Xeon E5-2650v2 processors (2.6 GHz, eight cores) and at least 64 GB RAM. As for used software tools: the GA was implemented in C++, the simulation model was created with AnyLogic 7 (JAVA), and the communication between the two was handled by Google Protocol Buffers 3.10.0.

5 COMPUTATIONAL RESULTS

Table 2 contains the results of five independent and reproducible optimization runs per test instance (the best result per instance is highlighted in **bold**). These results are compared with what we refer to as *intuitive solution* corresponding to a single replacement line that covers exactly the closed subway section. When compared to that solution, the west instance could be improved by 5.31% on average (5.83% best). The greatest improvement was accomplished on the north instance (9% on average, 9.84% best). Last, the big center instance was improved by 5% on average (5.32% best).

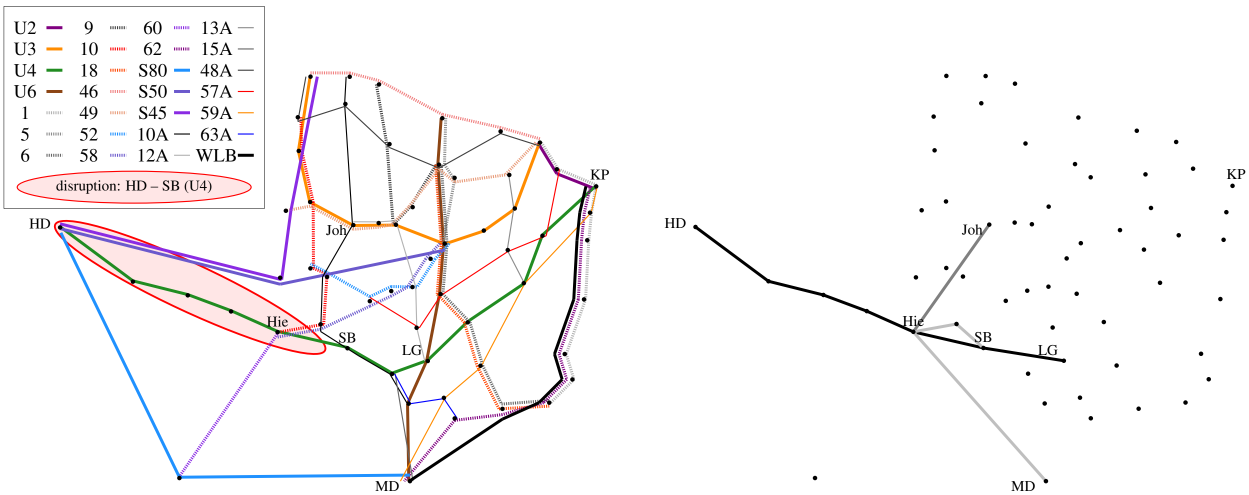
Now a closer look on the resulting best replacement lines: Figures 6, 7 and 8 contain the network and the resulting best replacement lines for each test instance. The best solution for the west instance (Figure 6b) has three replacement lines. One covers the disrupted section between Hütteldorf (HD) and Schönbrunn (SB), continuing to Längenfeldgasse (LG), thereby strengthening the connection to this important subway crossing station. The second replacement line connects Schönbrunn (SB) with Meidling (MD) via Hietzing (Hie). Apart from a small detour, this section is also covered by the first replacement line, but because the demand between Hietzing (Hie) and Schönbrunn (SB) is quite high, this redundancy makes perfect sense. A third replacement line connects Hietzing (Hie) to Johnstraße (Joh) and creates a welcome connection to the U3 subway line.

Figure 7b depicts the best solution for the north test instance. Similar to the west instance, first a replacement line covering the affected section is introduced. It goes from Hütteldorf (HD) to the Schottenring (SR), continuing to Schwedenplatz (SW) where the U1 and U4 subway lines intersect. A second replacement line connects Schottenring (SR) to the west.

Table 2: Tabular results: comparison to intuitive solution.

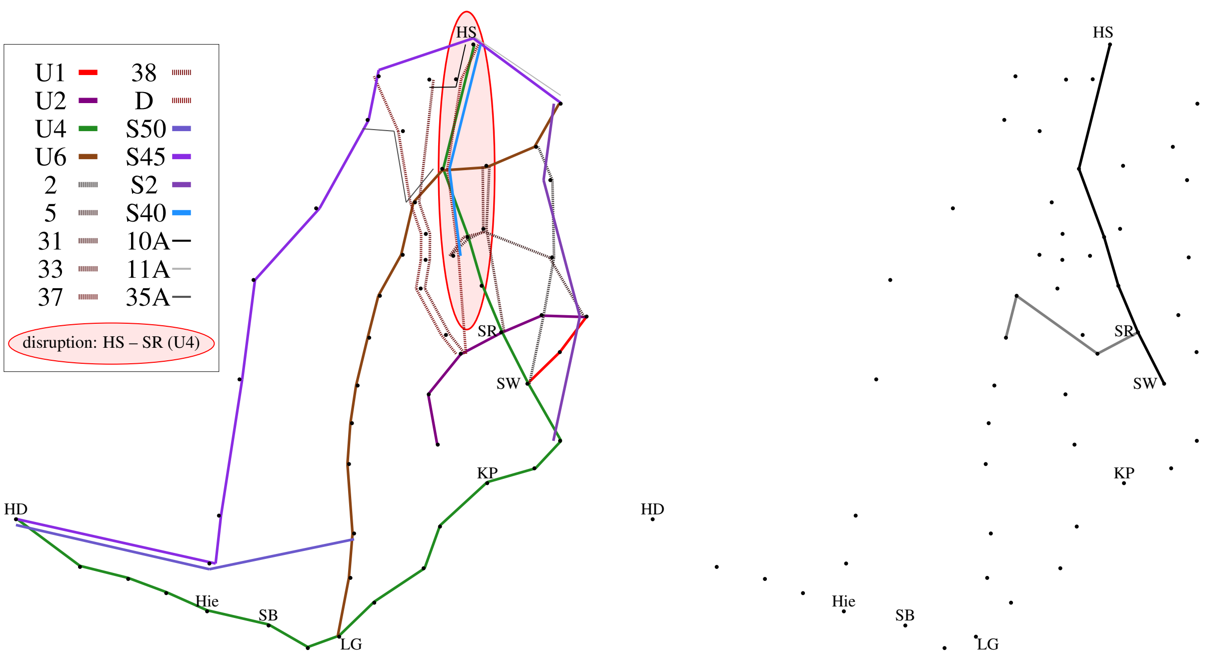
test instance		mean travel time per affected passenger [minutes]							diff. to intuitive sol.	
name	Figure	intuitive sol.	run 1	run 2	run 3	run 4	run 5	average	best	average
west	6	21.13	19.94	20.07	20.05	**19.90**	20.07	20.01	-5.83%	-5.31%
north	7	21.17	19.24	19.28	19.41	**19.09**	19.30	19.26	-9.84%	-9.01%
center	8	24.97	23.67	**23.64**	23.93	23.65	23.68	23.72	-5.32%	-5.02%

Last, the best replacement lines for the big center test instance are shown in Figure 8b. Once more, first a replacement line connecting the affected section between Karlsplatz (KP) and Längenfeldgasse (LG) is introduced. Again, the replacement line goes beyond the disrupted section, thereby creating a better connectivity. A second replacement line connects Schönbrunn (SB) via Längenfeldgasse (LG) to Hauptbahnhof (Hau), which is Vienna's central rail station.



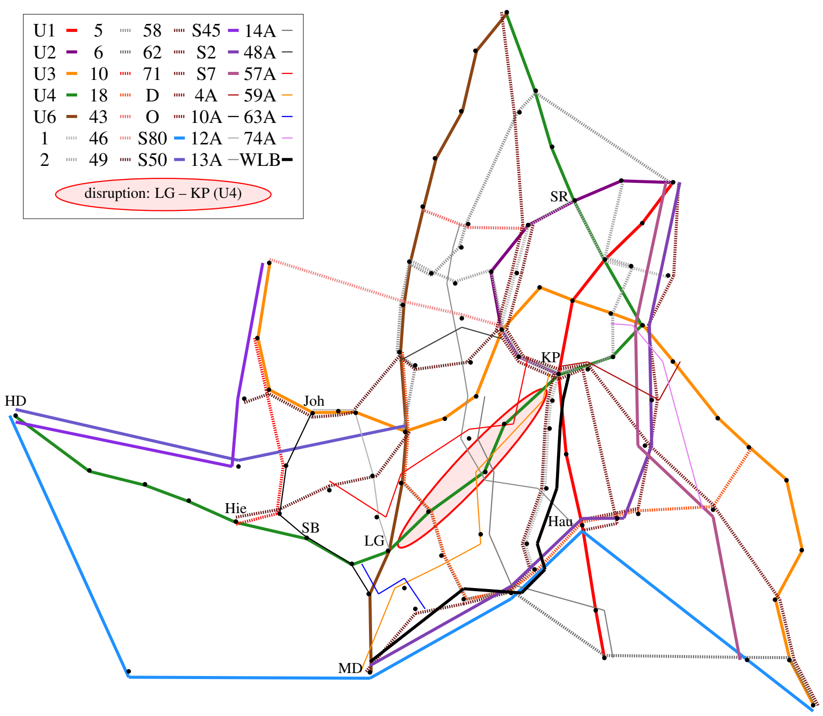
(a) West instance. (b) Replacement lines.

Figure 6: West instance (a) and best solution (b).

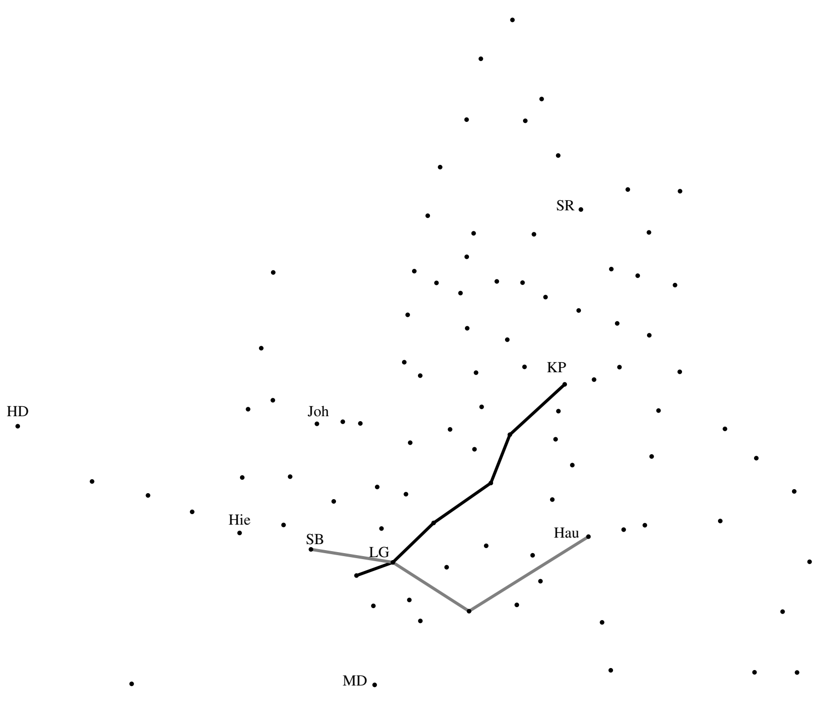


(a) North instance. (b) Replacement lines.

Figure 7: North instance (a) and best solution (b).



(a) Center instance.



(b) Replacement lines.

Figure 8: Center instance (a) and best solution (b).

In all three cases a replacement line covering the affected section plus one highly frequented station nearby is created. At least one more replacement line creates better connectivity to other cardinal directions and strengthens other connections with high passenger volumes.

Table 3 demonstrates the importance of both the pre-evaluation phase and the feedback mechanism of the algorithm. For that purpose the best and the average results of five runs of different settings of the algorithm are presented for each instance. The column *original* shows outcome of the original version as described in Section 3. The columns *w/o pre* and *w/o fb* refer to the version without the pre-evaluation phase and without the feedback mechanism, respectively. Clearly, the solution quality deteriorates when either of the features are deactivated.

Table 3: Comparison of different settings of the algorithm (mean travel time per affected passenger).

avg. travel	west			north			center		
time [minutes]	original	w/o pre	w/o fb	original	w/o pre	w/o fb	original	w/o pre	w/o fb
best	19.90	20.07	20.03	19.09	19.22	19.13	23.64	23.75	23.68
avg.	20.01	20.24	20.10	19.26	19.25	19.37	23.72	24.23	23.96

6 CONCLUSION AND PERSPECTIVES

The approach reduces the average travel time of the passenger affected by 5% (west and center instance) to 9% (north instance). One of the replacement lines in all three instances covered the disrupted section and reached beyond in order to improve connectivity. Additional replacement lines further improved the solution quality by reaching out in other directions and creating additional connections to important crossing stations. The problem-specific GA did significantly improve the solution quality.

As for the future, the accuracy could be improved by using raw data for railway, tramway and bus traffic. Furthermore, the use of stochastic elements could be extended to other areas, e.g., the free vehicle capacity calculation driven by passengers not affected by the disruption and the respective line's headway.

Public transportation networks are an important part of urban areas and are important for successful cities. Because of the many challenges that arise from the process of public transportation planning, and new possibilities driven by digitalization, fifth generation of wireless communications technologies, etc. this field of study is going to continue to be of interest for society and researchers alike.

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