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A DISCRETE EVENT SIMULATION MODEL OF THE VIENNESE SUBWAY SYSTEM FOR DECISION SUPPORT AND STRATEGIC PLANNING

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ABSTRACT

In this paper, we present a discrete event simulation model of the Viennese subway network with capacity constraints and time-dependent demand. Demand, passenger transfer and travel times as well as vehicle travel and turning maneuver times are stochastic. Capacity restrictions apply to the number of waiting passengers on a platform and within a vehicle. Passenger generation is a time-dependent Poisson process which uses hourly origin-destination-matrices based on mobile phone data. A statistical analysis of vehicle data revealed that vehicle inter-station travel times are not time- but direction-dependent. The purpose of this model is to support strategic decision making by performing what-if-scenarios to gain managerial insights. Such decisions involve how many vehicles may be needed to achieve certain headways and what are the consequences. There are trade-offs between customer satisfaction (e.g. travel time) and the transportation system provider's view (e.g. mileage). First results allow for a bottleneck and a sensitivity analysis.

1 INTRODUCTION

The Viennese subway network has 5 lines and consists of 90 *physical* stations, 10 of which are *crossing stations* where 2 or – in one single case – 3 lines meet. Table 1 contains some facts and figures on the subway system. Figure 1 depicts a stretched schematic plan of the Viennese subway network. Since this paper is going to look into the details of certain stations, *three* have been marked with icons representing a respective close-by landmark. marks *Stephansplatz* (i.e. the city center) and its renowned landmark St. Stephen's Cathedral. marks *Praterstern* and its landmark the Viennese ferris wheel. is a highly frequented train station called *Westbahnhof*. All three stations are highly frequented crossing stations.

Headway optimization is a significant subject in urban public transportation. Population growth – a prognosis expects the Viennese population (currently 1.78 millions) to break the 2 million mark by 2027 (Hanika 2015) – and reasons (efforts to reduce carbon emissions, improve the quality of life, tourism,

Table 1: Facts and figures on the Viennese subway system.

line name	line color	no. of stations	no. of max. active vehicles	line length [km]	[mi]
U1	red	19	26	14.54	9.04
U2	purple	17	19	12.60	7.83
U3	orange	21	22	13.40	8.33
U4	green	20	24	16.36	10.17
U6	brown	24	32	17.34	10.78
TOTAL			123	74.24	46.14

etc.) call for frequent re-evaluations whether provisions are – now or in future – indispensable. Economic factors – namely, capital and operational expenditure (including infrastructure preservation and potential expansion) – are contrary to the goal of passenger satisfaction (i.e. service level). This joint project is dedicated to solve these conflicting goals by determining the optimal hourly headways for each line.

This paper is structured as follows: Section 2 explains the problem of headway optimization. In Section 3 we describe the modeling approach, the detailed structure of the model and its entities. Section 4 discusses preliminary results, before Section 5 concludes the paper and presents future work.

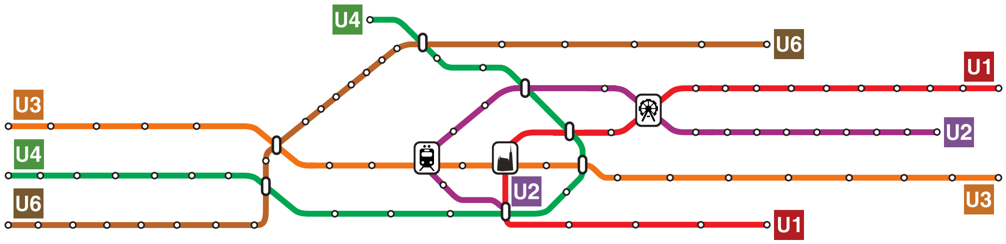


Figure 1: Stretched schematic plan of the Viennese subway network (as of 2012).

2 PROBLEM STATEMENT

According to Liebchen (2008), the *planning process in public transportation* comprises: 1) network design 2) line planning 3) timetabling 4) vehicle scheduling 5) duty scheduling and 6) crew rostering. The result of an earlier planning stage serves as an input for the subsequent tasks. *Headway optimization* is part of the task *timetabling* and one of three procedures of creating a schedule (Ceder 2001). Since a rapid transportation system like a subway system usually has a headway well below 10 minutes (especially during peak hours), passengers tend to ignore the schedule (Mandl 1980).

In order to model such a complex service system, *origin-destination-matrices* are needed. To the best of our knowledge, related contributions use count data (Ceder 1984), smart card data (Pelletier et al. 2009) and mobile phone data (Friedrich et al. 2010).

Another obstacle is modeling *passenger behavior*, especially how they decide which route they take (Agard et al. 2007). Raveau et al. (2014) show that there are also regional differences. For a study on various technologies used in pedestrian counting and tracking see Bauer et al. (2009).

The goals of this case study are to gain insights into the system's boundaries: First, whether there is room to improve *present day* system's performance by headway alterations and what are consequences in terms of number of vehicles, mileage and passenger satisfaction (passenger times). Second, *future-oriented* questions, namely: How many additional passengers can be handled under the current headway setting? In both cases, it is important to examine how certain key performance indicators (e.g. passenger times) interact. But there are of course conflicting goals: While passengers prefer tight headways which lead – up to a certain point – to reduced waiting and thereby a lower passenger travel time as well as low utilization, the Viennese public transportation provider has to operate in a resource-efficient way. To be able to answer those questions and derive strategic (and also tactical) actions, a decision support tool had to be developed as part of a joint project with the transportation network provider. That decision support tool is based on a model of the real world system.

Since the service system under consideration contains many stochastic elements (time-dependent Poisson processes, passenger as well as vehicle times) that preclude the application of analytic methods like Jackson networks (Jackson 1963) and its extensions, we resort to a simulation model.

3 SIMULATION MODEL

This section introduces the model and its components. It explains the structure (Subsection 3.1) and its interaction with moving entities – i.e. passengers and vehicles (Subsections 3.2 and 3.3 respectively). The simulation model was implemented in AnyLogic (version 7.0.3) and uses JGraphT (version 0.9.1).

3.1 Subway Network Modeling

Figure 2 depicts the basic structure of the subway network model: In this small example, we have 2 lines, a *white* and a *gray* one. Each of these lines comprises several *logical* stations (l_i). Except for end of lines (i.e. l_0, l_4, l_5 and l_9), every *logical* station is connected to two other *logical* stations. Such a connection consist of two *directed* arcs, thereby allowing vehicles to run in both directions. All end of line stations are equipped with a third *directed* arc that allows vehicles to perform a turning maneuver (i.e. loop back in the opposite direction). Every *logical* station is also assigned to a *physical* location (p_j). In case two or more *logical* stations share the same *physical* location (i.e. p_2), additional *directed* arcs (gray dotted arrows) allow passengers to transfer from one line to another.

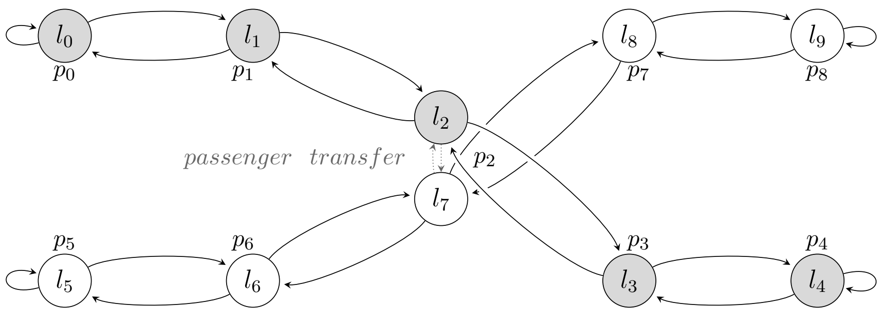


Figure 2: Schematic example of two intersecting lines.

Each *logical* station is divided into an *upstream* and a *downstream* direction. Every direction has its own queue for *waiting passengers* whose capacity depends on its respective surface area. Since *alighting passengers* either leave the station or transfer to another line, and thus do not spend much time on the platform, we assume that they do not interfere with the *waiting queue*. In order to make sure that there is still enough space for alighting passengers, we only allow two waiting passengers per square meter (1.2yd^2). Figure 3 illustrates the aforementioned principle of passenger/vehicle interaction. Notice, that of course the alighting passengers first leave a vehicle before waiting ones board it.

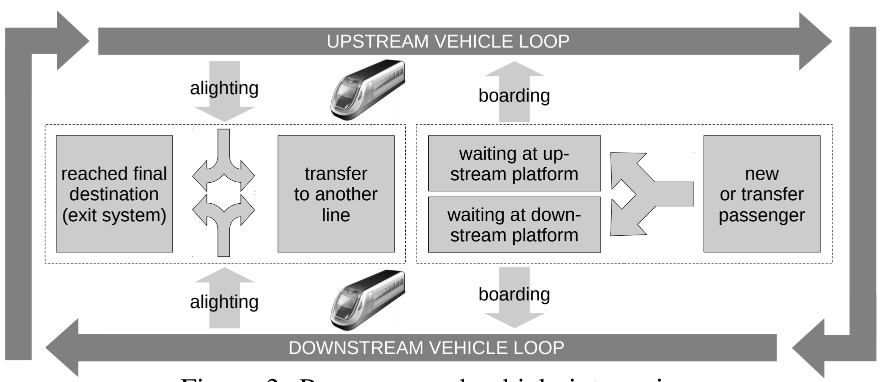


Figure 3: Passenger and vehicle interaction.

3.2 Passenger Modeling

Passenger generation is driven by a time-dependent Poisson process that starts at 04:50 am and continues until 01:00 am. This time frame is divided into intervals of one hour for which a respective origin-destination-matrix provides the hourly passenger rates (FFG 2010).

Figure 4 depicts the number of passengers within the Viennese subway system over operating hours. Like in Niu and Zhou (2013) and Sun et al. (2014) the daily passenger volume has two spikes: One in the morning and one in the afternoon. In total, 1.7 million passengers – or rather journeys – per day are processed by the subway system. The model is a replay of Tuesday 26th of June 2012, which was an ordinary work- and schoolday. To the best of our knowledge, there were no mass events on that day.

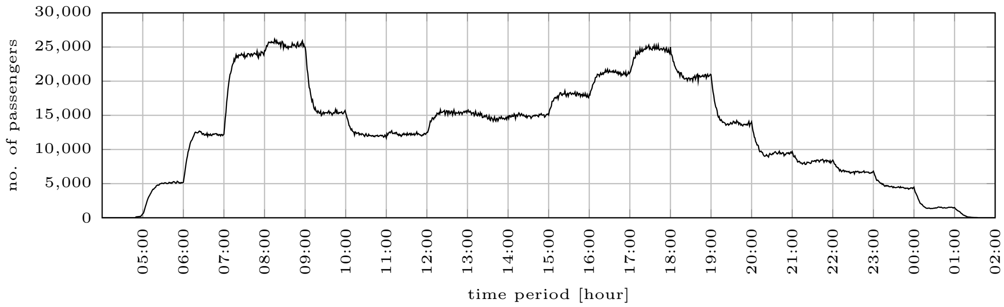


Figure 4: Number of passengers over time.

Once a passenger entity has been created, it is equipped with a route that consists of *logical stations*. For example, a passenger whose *physical* origin is p_0 and who whats to travel to the *physical* destination p_8 would have to travel the *logical* stations l_0, l_1, l_2, l_7, l_8, l_9. At p_2, the passenger performs a transfer from l_2 to l_7. To achieve this, the *physical* origin and destination is transformed into a path of *logical* stations which includes only *logical* origin and destination stations and – if needed – *logical* transfer stations. In this case, the designated *passenger path* is: l_0, l_2, l_7, l_9. These passenger routes are generated by a shortest path algorithm. The underlying graph has *non-transfer* edges (used by vehicles) and *transfer* edges (used by passengers). The latter have a higher weight, thereby penalizing transfers. Without penalizing transfers, passengers would be tempted to perform unnecessary transfers. If, for example, passengers want to go from one end of the green line U4 (Figure 1) to the other, they might be tempted to mistakenly take a shortcut via the red U1.

The structure of the aforementioned *passenger path* (i.e. pairs of logical origin or transfer origins and logical destinations or transfer destinations) allows us to determine whether a passenger comes from a line's *upstream* or *downstream* direction. This is vital to determine the correct transfer time. An example: At Praterstern the U1 has a side platform, the U2 an island platform. A transfer from U2 to U1 *upstream* (westbound) and vice versa take an average of 3 minutes. Transferring from U2 to U1 *downstream* (eastbound) and vice versa takes 3.75 minutes.

According to Weidmann (1994), a passenger's mean walking speed is 1.34 m/sec. (1.47 yd/sec.) with a deviation of $\pm 19\%$. Construction plans were used to measure the distance from the middle of one 115 meter (126 yard) long platform to the middle of another line's platform. Then, the aforementioned walking speed is used to calculate the mean transfer time. The model uses a triangular distribution with the measured mean and $\pm 20\%$ as minimum/maximum.

3.3 Vehicle Modeling

The Viennese subway network operates with two different types of vehicles. The vehicle type used on lines U1 to U4 has a passenger capacity of 878 passengers. The second vehicle type is employed only on line U6 and has a capacity of 776. Each vehicle is assigned to a specific line as well as a starting station. Vehicles always begin and end their tour at either one of the end of line stations. They are released in accordance with the respective line's current headway. These headways potentially change hourly so as to meet the time-dependent demand (i.e. hourly passenger volume).

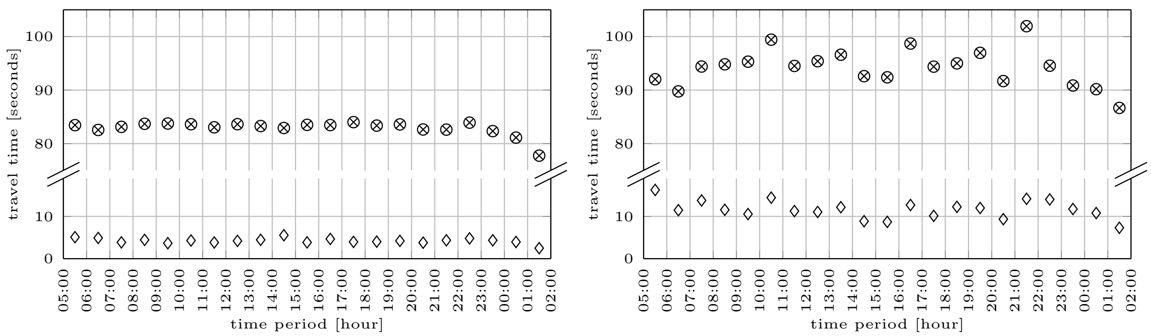
Since the infrastructure allows for a minimum headway of 1.5 minutes, a vehicle is not allowed to leave a station before 90 seconds have elapsed since the departure of the preceding vehicle. Note that this does not apply to the vehicle release at end of line stations. Furthermore, no more than two vehicles can be on route from one station to the next. Hence, if the headway is lower than 1.5 minutes, bunching phenomena occur.

Definition 1 The term *vehicle inter-station travel time* is used to refer to the time difference between a vehicle's arrival at one station and its arrival at the following station. The *dwelling time* at the first station is thereby already included.

Definition 2 The term *dwelling time* is used to refer to the time difference between a vehicle's arrival at a station and its departure. It includes the boarding and alighting time.

Definition 3 The term *boarding and alighting time* is used to refer to the time difference between a still-standing vehicle opening its doors, thereby allowing aboard passengers to alight and waiting passengers to board the vehicle, and closing them again.

To create a realistic model, the vehicle travel time had to be determined. Since this is neither a micro-simulation nor a physical model, no vehicle speeds (including acceleration and deceleration) were implemented. A comprehensive statistical analysis of vehicles' station arrival times (about 2,500 samples per section) revealed that the vehicle travel time between two consecutive stations does not depend on the *time of day* but rather on the *direction*. Figure 5 depicts this effect: One would presume that the vehicle travel time would suffer from the effects of increased passenger volume at peak hours (i.e. increased dwelling time). Surprisingly, this is not the case: Whenever the dwelling time is longer than expected,



(a) Praterstern $\Longrightarrow$ Nestroyplatz. (b) Nestroyplatz $\Longrightarrow$ Praterstern.

Figure 5: Vehicle inter-station travel time: mean ($\otimes$) and deviation ($\diamondsuit$) over time (Praterstern, U1).

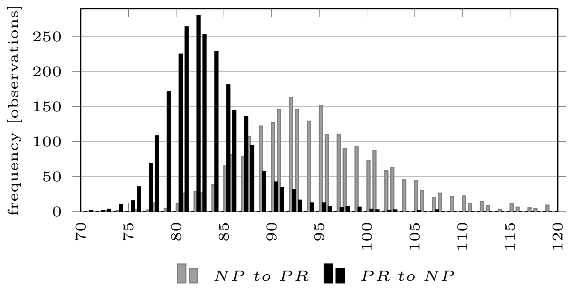
the driver is able to compensate for the time loss by increasing the vehicle's speed and vice versa. This analysis also reveals that the travel time depends on the direction in which the respective vehicle is moving.

Figures 5a and 5b illustrate this predicament: In both cases, there is no correlation between the inter-station travel time and peak hours. Most inter-station travel times over time look like Figure 5a. Figure 5b on the other hand is the most fluctuating one. According to the Viennese public transportation provider's experts, its cause is the change of drivers which happens at Praterstern in north-eastern direction. While Praterstern to Nestroyplatz takes an average vehicle travel time of about 84 seconds, the opposite direction takes 10 seconds more and has a higher deviation. What happens is, that drivers are eager to finish their last tour, but once the reach Nestroyplatz they realize that they are a bit early and decide to stay longer or decrease their speed in order to arrive at Praterstern punctually. This creates a certain degree of disturbance.

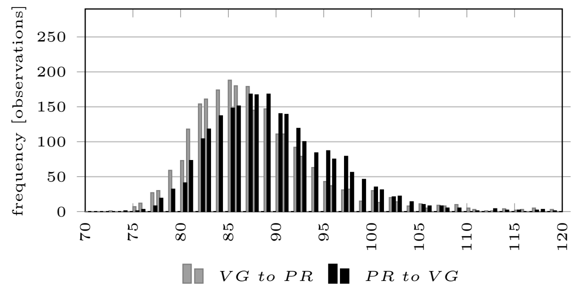
Figure 6a depicts the frequencies of observed travel times on the same section of the line. Most inter-station travel times are like in Figure 6b. Some stations – especially crossing stations close to the city center – have a longer vehicle travel time *away* from them than *towards* them. This is caused by longer dwelling times and Stephansplatz (Figures 6c & 6d) and Westbahnhof (Figures 6e & 6f) both share this phenomenon.

Since the majority of vehicle inter-station travel times appear to be almost *normally* distributed with a longer tail on the right side, we decided to use the *log-normal distribution*. Visual goodness-of-fit tests (Q-Q-plots, density-histogram plots, etc.) conducted in R provided strong support for this choice.

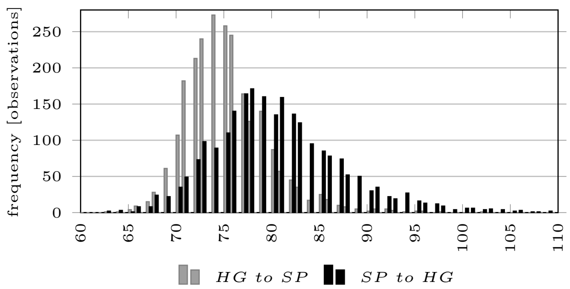
Once a vehicle has reached one end of a line, it first remains in the station for 0.41 minutes ($\pm$0.02). This is to account for about 25 seconds of dwelling time. Thereafter, the vehicle has to perform a turning maneuver. Depending on the infrastructure of the respective station and – in some cases – whether it is already after 20:30, this takes 4 to 8 minutes ($\pm$0.34 to $\pm$1.00). It is a matter of routine to turn vehicles



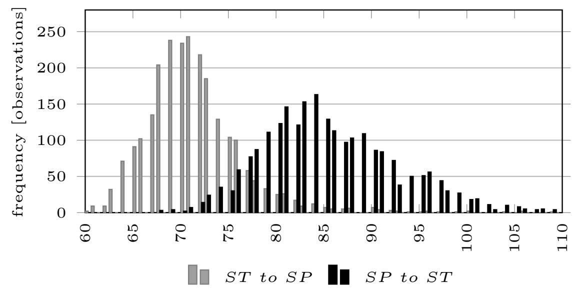
(a) Nestroyplatz ⇔ Praterstern (768m, 840yd).



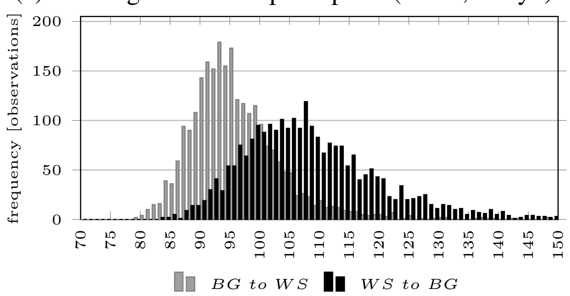
(b) Praterstern ⇔ Vorgartenstraße (715m, 782yd).



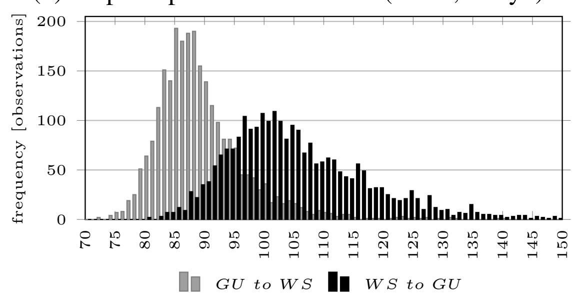
(c) Herrengasse ⇔ Stephansplatz (531m, 581yd).



(d) Stephansplatz ⇔ Stubentor (583m, 638yd).



(e) Burggasse ⇔ Westbahnhof (754m, 825yd).



(f) Westbahnhof ⇔ Gumpend. Str. (685m, 749yd).

Figure 6: Frequency of the vehicle travel time between Praterstern (U1), Stephansplatz (U3) as well as Westbahnhof (U6) and their respective adjacent stations.

after 20:30 simply by crossing over to the other direction's rail prior to the arrival at the last station. This saves time and consequently necessitates less vehicles. We employ *triangular* distributions for both.

We used selected vehicle-based key performance indicators, namely the *vehicle cycle time*, i.e. the vehicle travel time from one end of line station to another, and the *accumulated vehicle occupancy ratio* at crossing stations for validation (Table 2). The mean of the aforementioned cycle time (Table 2a) is a bit higher than the target values, but was approved of by the Viennese transportation provider's experts.

In Table 2b, we compared the resulting accumulated vehicle occupancy ratio. This ratio is based on counting data gathered from the vehicles' doors via infrared sensors. It expresses how big the share of

Table 2: Target versus simulation values (validation).

(a) Vehicle cycle time.

line	vehicle cycle time [min.]			
name	target	min	mean	max
U1	*26*	24.75	*26.15*	28.19
U2	*24*	23.08	*24.21*	26.64
U3	*26*	24.84	*26.41*	28.31
U4	*29*	27.98	*29.59*	31.28
U6	*34*	31.94	*34.68*	37.48

(b) Accumulated vehicle occupancy ratio.

crossing station	acc. vehicle occupancy ratio [%] target	simulation
Praterstern	8.70%	7.96%
Stephansplatz	7.41%	7.36%
Westbahnhof	6.67%	7.74%
Schwedenplatz	7.35%	7.30%
Karlsplatz	5.83%	5.10%
Schottenring	7.50%	7.52%
Volkstheater	7.35%	7.48%
Landstraße	6.04%	6.66%
Spittelau	3.62%	3.64%
Längenfeldgasse	6.54%	8.02%

a line's daily accumulated passengers onboard a vehicle at a certain station is. An example: If 10,000 passengers were onboard a vehicle at a certain station and 200,000 when counting the whole line, the station has a accumulated vehicle occupancy ratio of 5%. We compared the resulting values with counting data and also used this approach to adjust the *passenger routing* (see Section 3.2).

4 EXPERIMENTS AND RESULTS

In order to properly address the Viennese public transportation system provider's strategic goals (see Section 2), two scenarios were devised: The first is a parameter variation of the lines' respective *headways* (Section 4.1). In the second scenario, the *number of passengers* created is increased while the headways stay as they are (Section 4.2). Table 3 contains the original headways.

Table 3: Headways of the Viennese subway network (Monday – Thursday).

line name	headway [minutes] per timespan [from – to] 04:50 05:59	06:00 06:59	07:00 07:59	08:00 08:59	09:00 09:59	10:00 11:59	12:00 12:59	13:00 13:59	14:00 14:59	15:00 15:59	16:00 17:59	18:00 18:59	19:00 19:59	20:00 20:59	21:00 23:59	00:00 02:00
U1	6.25	2.75	2.50	3.00	4.00	4.00	3.65	3.30	3.30	3.00	3.00	4.15	5.00	6.25	7.50	15.00
U2	5.50	4.38	3.75	3.75	4.38	5.00	5.00	3.75	3.75	3.75	3.75	3.75	5.00	6.25	7.50	15.00
U3	5.00	4.50	3.00	3.00	3.50	4.00	4.00	4.00	3.00	3.00	3.00	3.50	4.50	6.25	7.50	15.00
U4	5.50	3.00	3.00	3.00	4.00	5.00	4.38	3.75	3.75	3.54	3.33	3.67	4.50	5.00	7.50	15.00
U6	5.00	2.75	2.50	2.50	4.00	4.00	3.50	3.00	3.00	3.00	3.00	3.00	4.00	5.00	7.50	15.00

Nearly 19% of all passengers perform at least one transfer to another line (16.5% one and 2.4% two). Each line either has a direct connection to other lines or an indirect one via *one* other line (Figure 1). Thereby, no more than two transfers are necessary. The mean and maximum transfer time per *transfer passenger* are 2.3 and 7.1 minutes respectively.

In both scenarios, 100 independent replications were made under each setting to account for stochastic variance. Since the deviation of mean values was well below 0.50% in most cases, they were not included in the upcoming result tables. The worst case in terms of standard deviation was the mean station utilization with 1.64% in the unlimited version of the passenger scenario.

Utilization is influenced by all created passengers, except for rejected ones. The term *rejected passengers* refers to passengers who were unable to reach a platform because its capacity had been exceeded (balking behavior). Only passengers who have finished their respective tour from origin to destination are included in passenger time statistics (traveling, invehicle, waiting and transfer time).

4.1 Headway Scenario

In this scenario, the hourly *headway* for each line is manipulated by multiplying the original values with a factor between 0.50 and 2.00 (in 31 steps à 0.05). Its goal is to determine the boundaries of the system in terms of feasible headway factors. Table 4 contains the results (in order to save space in steps à 0.15).

Table 4: Results of the headway scenario.

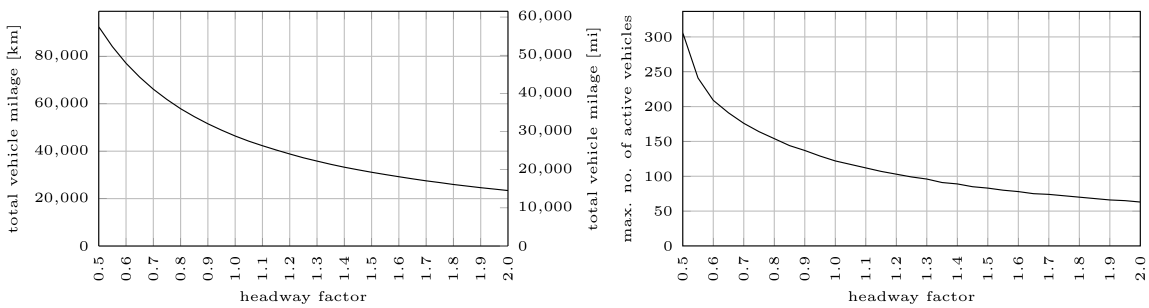
headway	mileage		rejected	active vehicles		travel time [min.]		invehicle time [min.]		waiting time [min.]		transfer time [min.]		acc. vehicle utilization [%]	
factor	km	miles	passengers	mean	max	mean	max	mean	max	mean	max	mean	max	mean	max
0.50	92,466	57,456	0	170	306	9.20	65.13	7.56	43.01	1.20	53.98	0.44	7.08	6.81%	12.35%
0.65	71,239	44,266	0	121	191	9.11	50.63	7.10	37.95	1.57	27.87	0.44	7.06	9.32%	16.10%
0.80	57,914	35,986	0	97	154	9.43	52.49	7.06	37.80	1.92	29.24	0.44	7.08	11.51%	20.01%
0.95	48,876	30,370	0	82	129	9.78	54.30	7.06	37.81	2.28	34.12	0.44	7.09	13.62%	24.02%
1.10	42,307	26,289	0	71	112	10.11	59.57	7.06	37.77	2.61	39.65	0.44	7.08	15.74%	27.93%
1.25	37,215	23,124	0	63	99	10.48	62.47	7.06	37.79	2.98	44.26	0.44	7.07	17.86%	31.86%
1.40	33,245	20,657	277	56	89	10.87	78.76	7.06	37.82	3.37	63.71	0.44	7.08	20.08%	36.56%
1.55	30,153	18,736	1,541	51	80	11.25	100.41	7.05	37.78	3.76	86.37	0.44	7.08	22.03%	40.04%
1.70	27,497	17,086	3,501	46	74	11.69	142.17	7.05	37.80	4.20	127.53	0.44	7.08	24.20%	44.32%
1.85	25,283	15.710	6,448	43	68	12.20	164.07	7.05	37.79	4.72	149.88	0.44	7.08	26.16%	48.27%
2.00	23,401	14,541	11,138	39	63	12.90	205.18	7.04	37.84	5.41	193.26	0.44	7.08	28.63%	52.60%

Figure 7a depicts how a tighter headway (i.e. a small headway factor) leads to a higher total vehicle mileage. Naturally, it correlates with Figure 7b. The maximum number of simultaneously active vehicles allows the determination of the required minimum size of the vehicle fleet.

The vehicle utilization (used in both scenarios) refers to the ratio between the total number of passengers onboard and the total capacity provided by currently active vehicles. Both are *accumulated* and refer to the whole network and not individual vehicles or stations. Figure 8a depicts how the vehicle utilization (mean and max.) are linear – higher headway factors result in less vehicles and thereby a higher utilization.

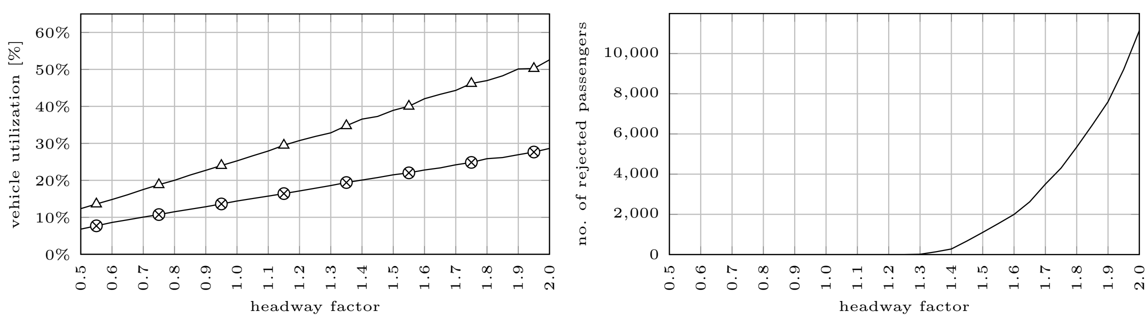
According to Figure 8b, a headway factor of 1.30 and above already leads to overcrowded stations.

Figure 9 illustrates what happens to passengers. Their mean travel time increases as they spend more and more time waiting and less within a vehicle. At a headway factor of 0.50 there is a slight but noticeable increase in passenger travel time caused by a higher invehicle time. This is due to a bunching phenomenon (Section 3.3). The transfer time stays as is since it is not affected by headway manipulation.



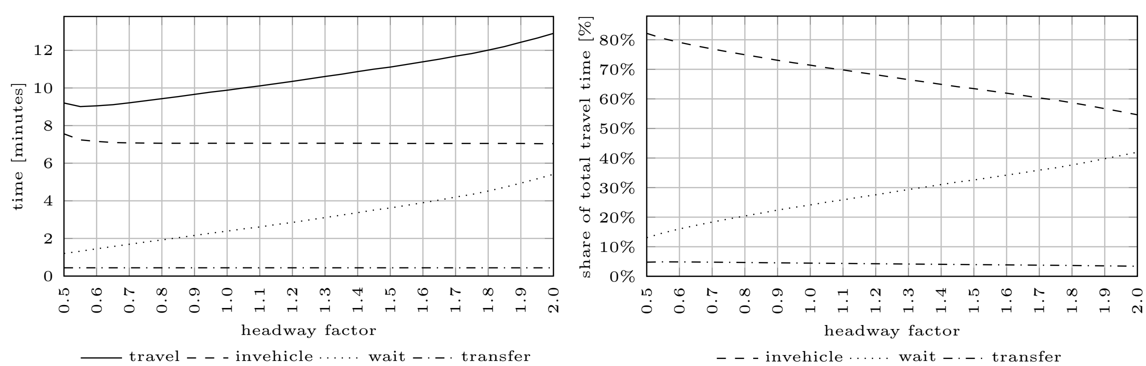
(a) Total vehicle mileage. (b) Number of max. active vehicles.

Figure 7: Total vehicle mileage as well as max. number of active vehicles over different headway factors.



(a) Vehicle utilization: mean (⊗) and max (△). (b) Number of rejected passengers.

Figure 8: Vehicle utilization (mean and max.) and rejected passengers over different headway factors.



(a) Passenger times absolute. (b) Passenger times ratio.

Figure 9: Passenger times absolute as well as their ratio over different headway factors.

4.2 Passenger Scenario

In the second scenario, the headways stay the same, but the passenger generation intensity is varied between 1.00 and 3.00 (in 41 steps à 0.05). The goal of this scenario is to determine bottlenecks and boundaries in terms of passenger volume (i.e. how much the network can handle with the current setting).

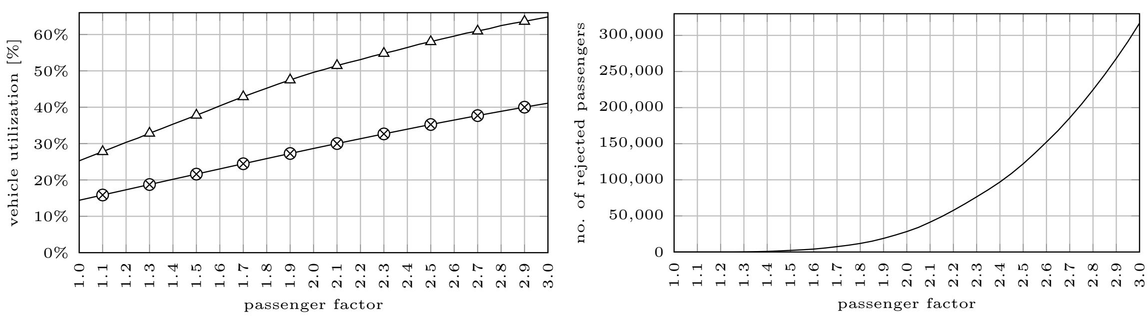
Since *passenger times* (travel, waiting, invehicle and transfer time) behave similarly to the previous *headway* scenario (Section 4.1), this scenario is executed with and without station capacity restrictions. Table 5 contains the results (in steps à 0.15) of the passenger scenario (limited station capacity).

Table 5: Results of the passenger scenario (limited station capacity).

passenger factor	rejected passengers	travel time [min.] mean	travel time [min.] max	invehicle time [min.] mean	invehicle time [min.] max	waiting time [min.] mean	waiting time [min.] max	transfer time [min.] mean	transfer time [min.] max	acc. station utilization [%] mean	acc. station utilization [%] max	acc. vehicle utilization [%] mean	acc. vehicle utilization [%] max
1.00	0	9.88	56.01	7.06	37.76	2.39	33.40	0.44	7.06	1.44%	2.86%	14.41%	25.26%
1.15	0	9.89	56.36	7.06	37.84	2.39	32.69	0.44	7.10	1.66%	3.31%	16.58%	29.05%
1.30	123	9.91	64.81	7.06	37.85	2.41	49.81	0.44	7.09	1.89%	4.12%	18.74%	32.84%
1.45	1,551	9.94	81.46	7.06	38.05	2.44	64.67	0.44	7.10	2.13%	4.96%	20.89%	36.56%
1.60	4,054	9.96	101.63	7.05	38.08	2.47	85.65	0.44	7.11	2.38%	5.69%	23.03%	40.37%
1.75	9,445	10.02	137.65	7.05	38.00	2.53	121.82	0.44	7.10	2.67%	6.64%	25.16%	44.07%
1.90	18,868	10.17	158.32	7.05	38.21	2.68	143.01	0.44	7.12	3.07%	7.67%	27.27%	47.50%
2.05	34,096	10.34	178.32	7.04	38.13	2.86	162.57	0.44	7.13	3.51%	8.48%	29.33%	50.47%
2.20	57,663	10.50	197.62	7.04	38.14	3.02	181.54	0.44	7.13	3.96%	9.93%	31.34%	53.09%
2.35	86,276	10.67	220.46	7.03	38.15	3.20	203.55	0.43	7.14	4.46%	11.10%	33.31%	55.56%
2.50	122,130	10.92	314.34	7.02	38.14	3.47	292.33	0.43	7.14	5.11%	13.57%	35.24%	58.03%
2.65	168,190	11.18	354.23	7.02	38.25	3.73	331.76	0.43	7.14	5.79%	16.45%	37.09%	60.35%
2.80	224,563	11.44	369.17	7.01	38.32	4.00	345.83	0.43	7.14	6.50%	18.51%	38.87%	62.45%
2.95	291,434	11.74	379.30	7.00	38.30	4.31	356.38	0.42	7.16	7.32%	20.03%	40.57%	64.22%

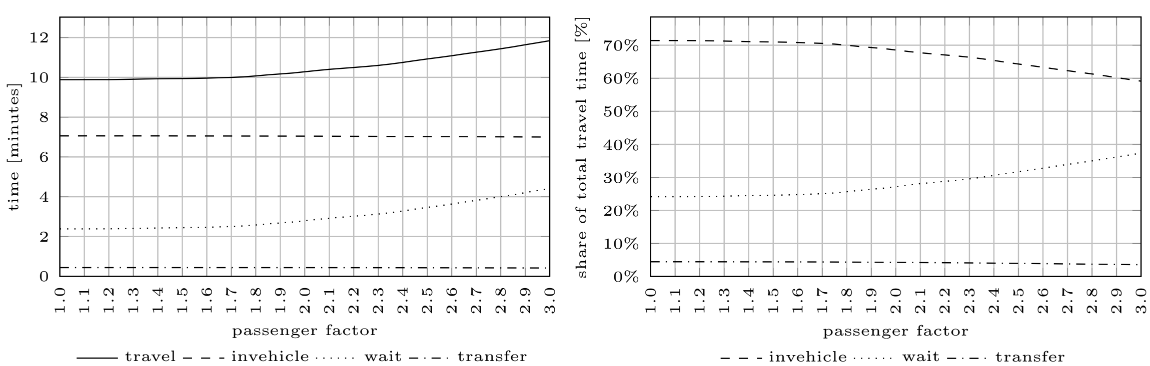
Figure 10a depicts the vehicle utilization. Contrary to the headway scenario (see Figure 8a), the maximum vehicle utilization is no longer linear. Up to a passenger factor of 1.75 it still is, but after that the increased number of passengers cannot continue to keep it linear. This is due to the low vehicle utilization at the outer stations – even if their passenger volume is increased up to 300%. As for rejected passengers (Figure 10b), at a passenger factor of 1.30 and above, there are more and more overcrowded stations.

Figure 11 shows the passenger times that are pretty similar to those obtained in the headway scenario (see Figure 9). Again, the travel time increases due to longer waiting times – especially with a passenger factor higher than 1.80.



(a) Vehicle utilization: mean (⊗) and max (△). (b) Number of rejected passengers.

Figure 10: Vehicle utilization and rejected passengers over passenger factors (limited station capacity).



(a) Passenger times absolute. (b) Passenger times ratio.

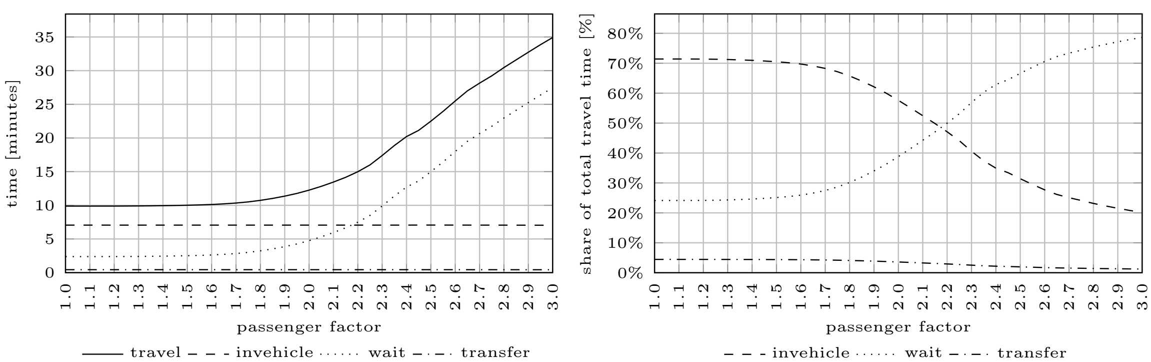
Figure 11: Passenger times absolute as well as their ratio over passenger factors (limited station capacity).

Table 6 contains the results of the unlimited version of the passenger scenario (again, in steps à 0.15 to save space). Instead of *rejected* passengers, this version has *abandoned* passengers (i.e. passengers who remain in the system and do not get picked up due to overcrowded vehicles). Since the vehicle utilization in the unlimited version is quite close to the limited one (see Table 5 and Figure 10a), we refrained from creating a separate plot.

Table 6: Results of the passenger scenario (unlimited station capacity).

passenger factor	abandoned passengers	travel time [min.] mean	travel time [min.] max	invehicle time [min.] mean	invehicle time [min.] max	waiting time [min.] mean	waiting time [min.] max	transfer time [min.] mean	transfer time [min.] max	acc. station utilization [%] mean	acc. station utilization [%] max	acc. vehicle utilization [%] mean	acc. vehicle utilization [%] max
1.00	27	9.88	56.01	7.06	37.76	2.39	33.40	0.44	7.06	1.44%	2.86%	14.41%	25.26%
1.15	32	9.89	56.36	7.06	37.84	2.39	32.69	0.44	7.10	1.66%	3.31%	16.58%	29.05%
1.30	36	9.91	65.47	7.06	37.97	2.41	50.42	0.44	7.10	1.89%	4.14%	18.74%	32.80%
1.45	39	9.98	99.81	7.06	38.05	2.48	84.03	0.44	7.10	2.17%	5.49%	20.90%	36.63%
1.60	45	10.12	146.37	7.06	38.10	2.62	131.15	0.44	7.12	2.54%	7.20%	23.07%	40.38%
1.75	49	10.51	222.05	7.06	38.04	3.01	206.19	0.44	7.10	3.18%	10.20%	25.25%	44.12%
1.90	52	11.36	295.17	7.06	38.12	3.86	277.81	0.44	7.12	4.44%	13.94%	27.44%	47.51%
2.05	56	12.82	346.26	7.06	38.13	5.32	327.56	0.44	7.11	6.58%	17.80%	29.65%	50.49%
2.20	59	14.99	409.93	7.06	38.15	7.49	390.37	0.44	7.12	9.95%	22.34%	31.90%	53.23%
2.35	1,758	18.87	810.19	7.06	38.12	11.38	799.53	0.44	7.13	16.23%	32.92%	34.30%	55.89%
2.50	21,820	22.49	977.99	7.07	38.15	14.99	969.61	0.44	7.15	25.41%	52.60%	36.69%	58.46%
2.65	52,073	26.99	992.53	7.06	38.24	19.50	983.43	0.44	7.14	36.64%	74.72%	38.95%	60.49%
2.80	99,113	30.46	998.43	7.05	38.26	22.97	989.43	0.44	7.15	49.57%	97.83%	40.98%	62.56%
2.95	160,177	33.85	1,007.25	7.04	38.32	26.38	997.63	0.43	7.17	64.75%	124.68%	42.81%	64.14%

Figure 12 contains the results of the unlimited passenger scenario. Once again, the travel time increases due to higher waiting times. At a passenger factor of 2.20, the average passenger spends more time waiting than within a vehicle. There are also not enough vehicles (e.g. too many passengers) to empty the subway network before closing time. This effect already starts at a passenger factor of 2.35 (1,758 abandoned passengers). This is also the reason for a slight drop in mean transfer time: At a passenger factor of 2.35 and higher (in case of the limited version) and at a factor of 2.85 and higher (unlimited version) there are so many rejected or still waiting passengers – especially transfer passengers – that even the usually stable mean transfer time of 0.44 starts to drop.



(a) Passenger times absolute. (b) Passenger times ratio.

Figure 12: Passenger times absolute and their ratio over passenger factors (unlimited station capacity).

5 CONCLUSIONS AND PERSPECTIVES

The *headway scenario* revealed that a headway factor lower than 0.55 leads to bunching of vehicles and in further consequence to increased passenger travel time. A headway factor of 0.80 would require at least 154 vehicles and would decrease the average passengers travel time by almost half a minute (∼5%). At a headway factor of 1.00 the Viennese public transportation provider needs 122 vehicles which almost coincides with the number given in Table 1 (123 vehicles). High headway factors on the other hand lead to overcrowded stations (factor of 1.30 and above). Furthermore, a factor of 1.20 already increases the mean passenger travel time by 0.5 minutes (∼5%). The maximum passenger travel time then increases by over 5 minutes and continues to get worse. These boundaries give the Viennese public transportation provider some idea of the positive and negative effects of headway alterations and provides us with an outline of a feasible solution space.

As for the *passenger scenario*: In the limited version, a passenger factor of 1.3 (about 2.2 million passengers) and above more and more stations are overcrowded. The Viennese public transportation provider could then adjust the headway or increase the station capacity (i.e. widening the platforms). The unlimited version gives one some idea of the boundaries of the latter solution: A passenger factor of 2.35 and above still leads to hundreds of abandoned passengers and the average passenger's travel time increases significantly after a factor of 1.75. The mean vehicle utilization (over all vehicles that are in transit) would be raised from 14% to 19% and the maximum even from 25% to 33%. Of course, the unlimited approach is unrealistic but allows for insights into the boundaries of the aforementioned solution.

In both scenarios, the U4, followed by the U6, were the first lines to suffer from overcrowded stations. This is to show that our scattergun approach leaves room for improvement: Future work will be geared towards embedding the simulation model into a simulation-based optimization approach, like in Fu (2002). Some related works already use simulation-based optimization on queuing networks (Vázquez-Abad and Zubieta 2005, Osorio and Bierlaire 2013, Osorio and Chong 2015). A metaheuristic (e.g., a genetic algorithm like in Yu et al. 2011) will perform the task of choosing new headways which will then be re-evaluated by the simulation model.

Other extensions concern the implementation of further details like the passenger distribution on the platform and the development of additional performance measures. For the time being, the real world system still remains unaffected by this case study. But possible future impacts are changes in the lines' respective hourly headways (i.e. a new schedule), planning of vehicle acquisition and training of conductors, infrastructure alterations, etc.).

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