Revealing Differences in Public Transport Share Through District-Wise Comparison and Relating Them to Network Properties

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Abstract

Sustainable transport is becoming an increasingly pressing issue, with two major pillars being the reduction of car usage and the promotion of public transport. One way to approach both of these pillars is through the large number of daily commute trips in urban areas, and their modal split. Previous research gathered knowledge on influencing factors on the modal split mainly through travel surveys. We take a different approach by analysing the "raw" network and the time-optimised trips on a multi-modal graph. For the case study of Vienna, Austria we investigate how the option to use a private car influences the modal split of routes towards the city centre. Additionally, we compare the modal split across seven inner districts and we relate properties of the public transport network to the respective share of public transport. The results suggest that different districts have varying options of public transport connections towards the city centre, with a share of public transport between about 5% up to a share of 45%. This reveals areas where investments in public transport could reduce commute times to the city centre. Regarding network properties, our findings suggest, that it is not sufficient to analyse the joint public transport network. Instead, individual public transport modalities should be examined. We show that the network length and the direction of the lines towards the city centre influence the proportion of subway and tram in the modal split.

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1 Introduction

Commute trips are defined as the daily form of travel between home and the place of work. In the context of sustainable transport, active (walking and biking) and public modes of transport are preferable for these daily trips since they reduce energy consumption, CO2 emission and traffic congestion. However, commuting by private car has several undeniable advantages: flexibility and independence, convenience, and often also time-saving compared to other means of transport. It is therefore not surprising that the proportion of car use for commuting often exceeds the share of public transport. Goodman [18] reports 67.1% of private motorized transport as the main mode to commute to work in the 2011 census in England and Wales, whereas in the US about 95% of the commutes are found to be by car [5]. In urban settings, however, there is also evidence, that public transport is frequently used for daily commuting [7, 24]. The question arises, which factors have an influence on the modal choices with respect to daily commutes? Wang and Liu [34] report a negative correlation between fare per kilometre and public transport use. Furthermore, as the top three influencing factors they found travel time, cost considerations and convenience of a private vehicle. Also having access to a car and/or a bike reduces the odds of using public transport [17, 19]. Recently, more attention has been paid to the connection between commuting mode choices and the built environment, including public transport infrastructure. The work of Yin and colleagues [37] suggests that car use could be reduced by balanced land use and improved residential density, whereas another recent study highlights the importance of proximity to stations and transportation service characteristics such as a low headway [19].

While most previous work regarding the modal split of commutes is based on humans' actual mode choices (as determined by travel surveys), our analysis examines the underlying network structure and focuses on the modal options the network theoretically offers to a commuter when optimising a route according to trip duration. First, we investigate the impact of owning a private car on the modal split. We do this by comparing two scenarios, one with and one without the car modality. This allows the examination of which district is public transport friendly. Additionally, we explore the relationship between network properties of the public transport network and the modal split of trips towards the city centre. Lastly, the focus lies in understanding how the network influences the share of public transport in order to positively affect the modal options of public transport. In the present work, the following research questions are addressed:

(1) How does owning a car influence the modal split of time-optimised routes?
(2) How does the modal split of trips towards the city centre correlate with spatial network properties of the public transport network in the origin district?
(3) Can we identify factors in the public transit network that hold the potential to increase the share of public transport?

2 Related Work

In the context of sustainable transport, the reduction of private car use is a key component. The most common alternatives to private motorised vehicles are either active means of transport, i.e. walking or biking, or the use of public transport. Sustainable transport and the promotion of public transport is by no means a new topic. In 2008, Eriksson and colleagues [14] conducted a study, where car drivers were asked for reasons that would make them reduce their car use for work commutes. Among the most frequent answers was improved public transport. About five years later, it was investigated which attributes of public transport attract car users [30] and it is concluded that improved quality of service has the potential to appeal to drivers. Around the same time, Goodman [18] analysed the 2011 census in England and Wales and reported strong car dependence for commuters, however, with a slight trend towards public transport. Likewise, the long-term trends in public transport demand are investigated [5]. For Germany and Canada, an increase in the percentage of workers using public transport is identified, whereas, for the US, no increase is present, with about 95% of commutes by car. Recently, this share has been confirmed [29].

Interestingly, for US cities, the city size does not have an impact on the car share, in contrast to cities outside the US, where size has a significant influence on the modal share. The authors also highlight the relationship between higher income and increased car usage.

One of the key factors highlighted by several studies concerning modal choices is travel time [25, 26, 34], which is found to influence the choice between private vehicle and public transport, even though the decision of an individual to travel by car is not always based on the goal to save time; flexibility and autonomy play a role, too [20]. Thus, a shift towards public transport might be achieved by providing fast public transport options that can compete with private cars. Additionally, reliable and affordable public transport and the limitation of motorised vehicles in high-density urban areas might help in promoting public transport [17, 34].

When trying to understand why people choose specific means of transport, the built environment plays a role, too, and it has been extensively studied in the transportation community [11, 35]. Where people live, work, and commute in the city plays a huge role in their choices between different modalities. A study conducted in the New York Metropolitan Region tried to understand the impact of density on mode choice decisions within home-based work tours. Noteworthy is the influence of employment density at workplaces, which surpassed that of residential density [9]. Another recent study has investigated the attributes of the built environment and the contextual effects that these have on humans travel behaviour [13]. With data from an online survey in Hamilton City Canada, they examined the determinants influencing mode choice behavior. Their findings suggest connections between sidewalk density and both walk and public transport usage. Loo and colleagues [24] summarize four dimensions that influence the number of railway passengers: land use, station characteristics, socio-economic and demographic characteristics and inter-model competition, with station characteristics being the most relevant one. When focussing solely on the public transport infrastructure, important characteristics include service quality, frequency and proximity to stops, as well as perceived safety at stations [10, 19]. Regarding upgrades in the public transport network, it has been shown that improvements in rail transit enhance the connectivity between homes and workplaces [16], highlighting the benefits of newly introduced lines.

Recently, some studies have investigated the share of transport modes in relation to different regions [2, 32]. They highlight differences in public transport accessibility (amongst others) in terms of connectivity, density and capacity. An analysis conducted in 2020 [6] focuses on differences in one single city and compares the 18 districts of Krakow in terms of public transport accessibility by employing seven major quantitative and five minor indicators that include characteristics of transportation services. The results highlight the quality of the transportation services and an interesting finding is that peripheral districts have better transportation services than the central district.

For the present work, especially the literature on travel time and public transport infrastructure is of interest. Since humans predominately prioritise the shortest possible travel time to arrive at a destination, we focus on time-efficient routes that a network provides for a commute from A to B, and we eliminate the need for travel surveys. Instead, we target the "raw" routing possibilities that the present street network and public transport infrastructure offer. The methodology we utilize for this work is purely algorithmic, focusing on revealing the network capacities in the best case, i.e. for a time during the day without traffic as well as public transport with a constant frequency and average waiting times at stations.

3 Case Study

To analyse the impact of spatial network characteristics on the modal options of commutes, a case study in the city of Vienna is conducted. Vienna is chosen since it is ranked among the best cities in terms of public transport [27], covering several different modes of transportation. The commuting trips are modelled as in-flow trips towards the city centre from the neighbouring districts. Since commuters might have different means of transport at hand (i.e. owning a car or not), two scenarios are investigated with the respective modes included in the multi-modal network: Scenario (a) - car, walk and public transport (bus, tram, subway and train) and Scenario (b) - walk and public transport only, excluding the car modality. Bike as an additional modality was not included (see Subsection 3.1 for reasoning). The multi-modal network hereby represents the actual streets and public transport infrastructure.

In this section, the four main processing steps are outlined. First, the data preparation is described, which is mainly concerned with creating the multi-modal network of the city of interest. Next, the route selection and the routing are introduced. Subsection 3.3 outlines how we incorporate human travel behaviour in the routing and finally, relevant descriptive network properties are discussed and it is hypothesised how they could relate to the routing results. Both the data and code for this work are available on our website[1].

3.1 Data Preparation

For the multi-modal routing, multi-graphs including several modes of transport are needed. Two private modes (car and walk) and four public modes (bus, tram, subway and train) are considered in the present work. Biking as an additional private mode was under consideration, however, we continued our analysis without including the bike mode based on the following findings: Since the trip distances of the present study are relatively short and the biking network is rather dense in Vienna, the fastest path to reach the destination is found to be bike only (i.e. a share of bike of 100%) for about 65% of the routes. Thus, any differences in the share of public transport would be hidden by a much higher share of bike.

The raw data necessary to construct the individual graphs for each mode of transport is downloaded from OpenStreetMap (OSM)[2] using the Overpass API and processed with custom Python scripts. Initially, a separate graph is created for each mode of transport. For the two private modes (car and walk), the edges of the graphs represent the street segments and the nodes represent the junctions. In the walking graph, also the stations of the public transport networks are part of the graph (as nodes), and they are connected via walkable edges to the rest of the walking graph. For the public transport networks, the edges represent the public transport lines and the nodes represent the stations. Each edge is assigned two attributes: *length* and *time*. The *length* attribute specifies the length of the respective segment geometry and is derived from the downloaded OSM data. The *time* attribute represents the duration needed to traverse this edge and the values are derived as follows: For the private modes (car and walk), the *time* attribute is computed by dividing the edge *length* by the respective speed. For the car graph, the speed is derived from the OSM tag *max_speed* (if not available: default to 30 km/h) and multiplied with a speed factor of 0.75, to account for acceleration and deceleration at intersections. The walking speed is

[1] `https://geoinfo.geo.tuwien.ac.at/resources/`
[2] © OpenStreetMap contributors, `https://www.openstreetmap.org`

based on the slope of the network edge, with 4.8 km/h for flat terrain and adjusted for every 5% of difference in inclination from -15% to 15% (see [4]). Additionally, for both modes, a traffic light penalty of 30 seconds is added on edges incoming to a traffic light [8, 28]. For public transport modes (bus, tram, subway, train), the *time* attribute reflects the duration to travel from one station to another and is derived from timetables, which were obtained in GTFS format from the public transport operators *Wiener Linien*[3] and *ÖBB*[4].

Once all individual graphs are processed, they are merged into a multi-graph. This is done by combining all individual graphs into one joined graph. To make it a routable multi-graph, transition edges between the individual modes are added. These transitions are possible at common nodes between two modes, so either at junctions that are both part of the car and the walk graph or at stations, that are both part of the respective public transport graph and the walk graph. For the costs of the transitions, the following modelling decisions are taken: For a transition from car to walking, the *time* attribute is set to 8 minutes, to model the time needed to find a parking space [3]. This transition is also counted length-wise as 3 additional kilometres travelled (*time* × default speed × speed factor). A reverse transition from walking to driving a car is not allowed (this imitates the characteristics of a one-way trip from A to B: once the private car is parked somewhere, it can not be used again to reach the destination). For a transition to a public transport mode, the cost assigned to that transitioning edge reflects the average waiting time for the next vehicle. It is modelled as half the headway [1], which is the average time between individual vehicles on a route. These headways are determined using the available GTFS timetables. When divided by two, the resulting average waiting times are the following: bus = 6.2 min, tram = 4.0 min, subway = 2.0 min and train = 5.9 min. Exiting public transport (i.e. a transition from a public transport mode to walking) is assigned a cost of Zero. To simulate the different availability of means of transport to commuters, two different multi-graphs are created:

1. a multi-graph comprising all six modes (car and walk as private modes; bus, tram, subway and train as public transport modes) for Scenario (a)
2. a multi-graph same as 1. but without car (so only walk and four public transport modes) for Scenario (b)

3.2 Route Selection and Routing

For the in-flow analysis of the current work, the first district of Vienna is chosen as the commuting destination, whereas seven districts are considered as origins. Thereby, only directly neighbouring districts to the centre are selected, as it minimizes the need to traverse other districts while finding the fastest route from origin to destination. These districts are the following: Leopoldstadt (2. district), Landstraße (3. district), Wieden (4. district), Mariahilf (6. district), Neubau (7. district), Josefstadt (8. district) and Alsergrund (9. district). Of these seven districts, district 2 is the largest, followed by district 3. Both of them have major subway lines running through them as well as central train stations in or in the vicinity of the district. District 8 is the smallest one, followed by districts 6 and 7. They are densely populated, with rather narrow and naturally developed streets. The districts on the western side of the city centre are dominated by trams and bus lines. Additionally, on the outer border, a subway line runs north-south and a major road aligns with it. Between the 9th and the 2nd district, a main road runs to the eastern part of the

[3] `https://www.wienerlinien.at`, GTFS data available at `https://www.data.gv.at/`
[4] `https://www.oebb.at`, GTFS data available at `https://www.data.gv.at/`

inner district. District 4 and 6 both have a high density of bus lines as well as subway lines running towards the centre. In between these two districts, a main artery leads towards the city centre. These differences in street layout and available public transport infrastructure make the inner districts an ideal area of interest for the present work. An overview of the district layout and the transport lines can be seen in Figure 1. For each of these seven districts, 500 Origin-Destination (OD) pairs are randomly chosen, with the origins in the respective district and the destination in the central district ($N = 3500$). Two additional conditions are applied to the route selection process: First, the beeline distance between the selected OD pairs needs to equal 3000 m $\pm$ 15 m (so 1% distance tolerance across OD pairs). This distance is chosen since it approximates the radius of the inner district ring of Vienna. Second, both the origin and the destination need to be reachable by car and foot. This is done to allow a fair comparison across the two private modes.

The routing is run for each of the two multi-graphs outlined in Subsection 3.1, for the same set of OD pairs. Dijkstra's shortest path algorithm [12] is used to compute the fastest paths with the weight set to *time*.

3.3 Human Travel Behaviour

Since we propose a purely algorithmic approach, without taking any surveys or human subject studies into account, we have to find another way to incorporate human travel behaviour and identify feasible routes. By feasible routes, we refer to routes that a commuter would actually choose, i.e. too many transfers or long distances by foot should be avoided. To approximate this human behaviour, we modify Dijkstra's algorithm to include so-called feasibility conditions: the maximum allowed walking distance is set to 1500 m [15, 33] and the maximum accepted number of transitions between modes is set to 4 [38]. If the fastest path exceeds these thresholds, the algorithm finds the next fastest path until it satisfies the two conditions, i.e. a feasible path is returned, that is both fast and viable for humans. With this approach, the resulting routes reflect the human travel behaviour and the analysis of the modal share is reasonable.

3.4 Descriptive Network Properties

To investigate how the modal split is influenced by the spatial properties of the existing public transport network, six metrics are proposed. Some of them are commonly used in literature as descriptive network measures, such as the number of stations (or station density) or the network length (or network density) [6, 31, 36], others we included based on our own considerations. More details on these considerations and hypotheses can be found below, where each property is introduced. A summary of all network properties can be seen in Table 1.

Each of the network properties is calculated for neighbourhoods around the route origins, considering the surrounding transportation networks within a 500-metre radius. This radius is chosen as an approximation of the distance a person is willing to walk. It is derived by dividing the maximum walking distance (1500 m [15, 33]) by three (a third for walking at the beginning of a route, a third at the end of a route and a third in between possible transitions). We assess the six metrics for both the entire public transport network and each mode separately (bus, tram, subway, and train). Next, we compute the Spearman correlation coefficient between each metric and the share of public transport. This analysis is conducted for the overall public transport share, including all modes, as well as specifically for the share of subway and tram, along with their respective properties. Bus and train are not correlated individually, since the proportion of them on the modal split is below an average of 1.60%.

Table 1 Descriptive network properties that are computed for the public transport networks, with the respective unit. Additionally, the expected correlation with the share of public transport is outlined (+ positive correlation, - negative correlation).

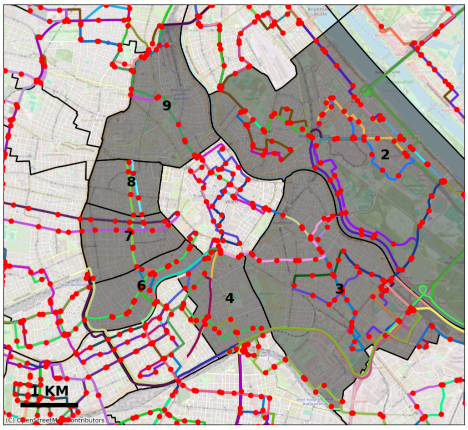
Network Properties	Unit	Exp. Correlation
number of stations	[#]	+
service area coverage	[%]	+
avg. line direction diff.	[°]	-
network length	[km]	+
minimum walk duration	[min]	-
number of lines	[#]	+

In the following, each property is introduced, with a reasoning why it is included and how it is expected to relate to the modal share. To illustrate some of the following considerations and allow a visual interpretation, the networks of the four modes of public transport are shown in Figure 1.

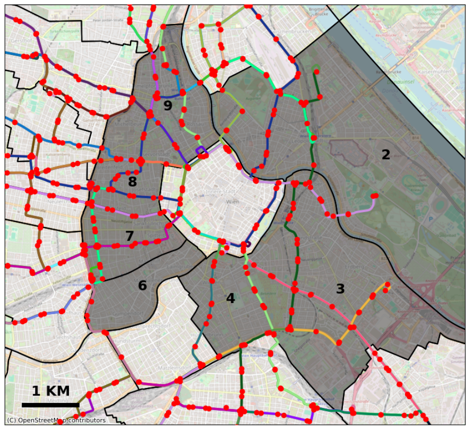
Number of stations. The number of stations represents the availability and accessibility of public transport. In the existing literature, this metric is often normalized by the area (station density) [6, 36], but since we consider the same neighbourhood extent around each origin, the number of stations allows a simpler interpretation. After visual inspection of Figure 1 (different zones contain a different amount of public transport stations), it is expected that the more stops there are in the vicinity of the starting point of a route, the higher the share of public transport. To derive this metric, the public transport stops in the respective 500 metre-neighbourhood are counted.

Service area coverage. The service area coverage characterizes how much of the surrounding area around an origin is suitable to reach a public transport stop within a given time. To compute this coverage, first, for each station within the buffer area, the reachable intersections are determined. This is called the service area of a public transport stop [21, 22]. A threshold value of 9.4 minutes is chosen, derived by dividing half of the allowed maximum walking distance by the average walking speed on flat terrain. Then, all these intersection nodes are enclosed with a convex hull. Finally, the convex hulls of all stations are spatially merged, and the service area coverage can be computed as the proportion of the whole buffer area. It is expected that a higher coverage is in favour of public transport since it ensures better access to public transport.

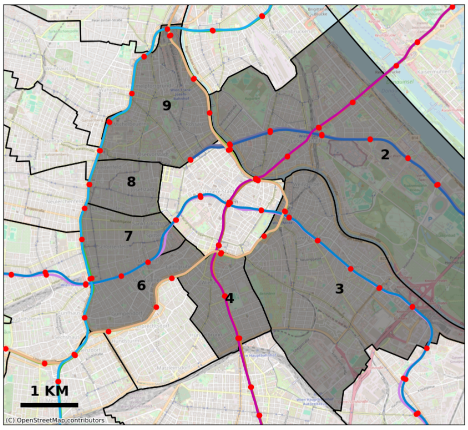
Average line direction difference. The average line direction difference is a self-derived measure intended to capture how well the directions of the existing lines agree with the overall direction from the origin to the centre. This measure was developed while investigating the existing layouts of the networks. In Figure 1 it can be seen that several lines are not oriented towards the centre, thus, even though there are nearby stations, they might be unsuitable to reach the first district. An example can be seen in the subway network (Subfigure 1c), with a line in the western part being oriented north-south. The computation of this property is as follows: First, for each origin, the beeline orientation to the centroid of the first district is computed. Next, for each line segment fully contained within the 500 metre-neighbourhood area, i.e. from one station to the next, the orientation is calculated and the difference to the main orientation of the respective origin is computed. All differences for one origin are



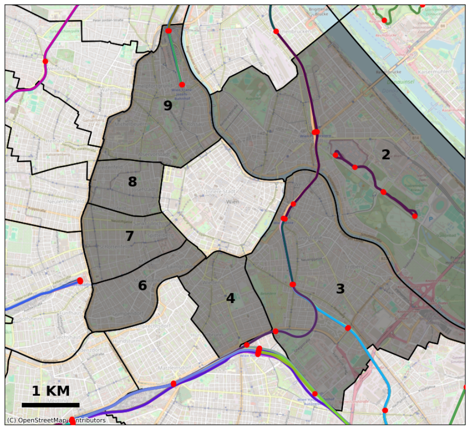
(a) Bus Network.



(b) Tram Network.



(c) Subway Network.



(d) Train Network.

Figure 1 Public transport networks in Vienna. The seven origin districts are highlighted in grey, stations are depicted in red and the different colours represent different public transport lines.

averaged. If no full line segment is within the buffer area, the metric is set to NaN. Since a lower mean difference shows a better agreement between public transport orientation and direction to the centre, a negative relation with the share of public transport is expected.

Network length. The network length is based on the network density [31]. The network density is computed as kilometres of links per square kilometres of surface and it is positively related to network development and economy. Since in the present work the metric is always computed for the same extent (buffer of 500 m around the starting node), not the density is considered but rather the absolute length of the network within this buffer area. Following the considerations of Rodrigue [31], a positive correlation between the network length and the share of public transport is expected.

Minimum walk duration. The minimum walking duration describes how far away (in terms of walking duration) the next public transport stop is located when starting from the origin. The lower the value, the higher the public transport share is expected to be, as it relates to easy access to public transport [10]. The metric is computed as the time needed to reach the nearest station. So, first, the walking duration to all stations within the 500 metre-neighbourhood is calculated, and then the lowest one is chosen as the minimum walk duration. All stations within the neighbourhood are considered, without taking the direction of the destination into account. If there is no public transport station within the area of interest around the origin, the metric defaults to NaN.

Number of lines. The number of lines represents the count of distinct public transport lines present in the 500 metre-neighbourhood of the origin. This property is closely related to the number of stations and the network length, however, it is expected to give further insight into the different options available to the commuter. A higher number of lines is assumed to positively influence the share of public transport. An example is given to elaborate on this consideration: If there are three public transport stations in the vicinity of the starting point, but they all belong to the same line (i.e. number of lines = 1), then this line is the only public transport option, but if there are three different lines available, it is more likely that one of these lines will be suitable for reaching the centre, as the number of options increases.

4 Results

This section presents the results of the routing and is divided into two subsections. The first subsection is concerned with the modal splits of both scenarios (with and without car modality), as well as the average trip durations and trip lengths. The second subsection outlines the network properties of the public transport networks and the correlation coefficients between each property with the share of public transport, again for the two scenarios.

Table 2 Scenario (a) - car, walk and public transport. Modal split (with the share of public transport also broken down into its individual components) and average trip duration and trip length per district and overall (all). Possible deviations from 100% are due to rounding errors.

	district							
	2	3	4	6	7	8	9	all
car [%]	51.00	65.25	52.64	42.09	78.32	94.92	87.78	66.82
walk [%]	10.68	6.56	10.02	12.42	4.41	0.58	2.17	6.84
public transport [%]	38.31	28.19	37.34	45.49	17.27	4.50	10.05	26.34
	=	=	=	=	=	=	=	=
- bus [%]	0.19	0.00	0.00	0.00	0.76	0.00	0.00	0.14
- tram [%]	0.65	2.29	1.80	0.04	0.34	4.15	0.00	1.30
- subway [%]	37.47	25.41	35.54	45.45	16.18	0.35	10.05	24.83
- train [%]	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.07
avg. duration [min]	21.04	20.68	20.79	21.83	21.86	20.24	20.02	20.93
avg. length [km]	5.81	6.06	5.59	5.70	6.71	7.14	6.94	6.26

4.1 Modal Split

First, the results for Scenario (a) are reported. Table 2 shows the results of the routing, where the underlying multi-graph includes the following modes of transport: car, walk, and public transport (bus, tram, subway, train). The share of car is the most noticeable at first, with an overall percentage of 66.82%. It differs across the different districts, with the lowest share in district 6 (42.09%) and the highest share in district 8 with 94.92%. Conversely, the share of public transport is highest for the 6. district with 45.49% and lowest in district 8

Table 3 Scenario (b) - walk and public transport only. Modal split (with the share of public transport also broken down into its individual components) and average trip duration and trip length per district and overall (all). Possible deviations from 100% are due to rounding errors.

	district							
	2	3	4	6	7	8	9	all
walk [%]	21.94	20.67	20.00	21.91	19.19	12.39	15.69	19.13
public transport [%]	78.06	79.33	80.00	78.09	80.81	87.61	84.31	80.87
	=	=	=	=	=	=	=	=
- bus [%]	4.02	2.99	0.16	0.97	2.50	0.00	0.00	1.60
- tram [%]	6.33	31.27	25.25	6.27	15.60	63.84	26.65	23.14
- subway [%]	67.70	40.63	54.60	70.84	62.71	23.77	57.66	55.56
- train [%]	0.00	4.44	0.00	0.00	0.00	0.00	0.00	0.57
avg. duration [min]	24.36	24.42	23.07	24.29	25.27	24.85	25.94	24.55
avg. length [km]	4.44	4.06	3.94	4.69	4.59	4.41	5.03	4.45

(4.50%). Looking at the detailed split by individual public transport modes, the share of subway takes the highest proportion for all districts except for district 8, where the share of tram (4.15%) is higher than the share of subway (0.35%). Bus and train do not exceed a share of 1% and have for several districts even a percentage of Zero. The share of walking is lowest in all districts, ranging from 0.58% (district 8) to 10.68% (district 2). The difference in average trip duration is rather small across all districts. It ranges from a minimum of 20.02 minutes (district 9) to a maximum of 21.86 minutes in the 7th district. The average trip length ranges from 5.59 km (district 4) to 7.14 km (district 8), this results in distance increases of up to 138% compared to the beeline distance of 3 km (see Table 4).

Next, we examine Scenario (b) - walk and public transport only. Table 3 presents the modal splits as well as the average trip durations and lengths. Since the car as a modal option is no longer available, both the share of walking as well as the share of public transport increase, with approximately 20% walking and 80% public transport. The share of public transport is lowest for the 2nd district with 78.06% and highest for district 8 (87.61%), with the respective remaining portion being walking. The detailed breakdown of the individual means of public transport provides additional in-depth insight. The two prominent modes are subway and tram, whereas bus and train show a very low presence. The share of bus ranges from 0.16% - 4.02%, with two districts not using buses at all. The train modality is even less common with only one district having a share of 4.44% (district 3). The proportion of tram ranges from 6.27% in the 6. district to 63.84% in district 8, whereas the share of subway extends over a span of 23.77% (district 8) to 70.84% (district 6). Similar to Scenario (a), the share of the subway is higher than that of the tram in all districts, with the exception of the eighth district, where the opposite is the case. The average trip duration is lowest for the 4th district at 23.07 minutes and highest for district 9 at 25.94 minutes. Similarly, also average trip length is lowest in district 4 and highest in district 9 (3.94 km and 5.03 km, respectively). Compared to the beeline distance of 3 km, the increase in distance ranges from about 30% to 67% (see Table 4).

Lastly, travel time ratio and travel distance ratio are depicted in Table 4. The ratios are computed by dividing the average duration (distance, respectively) of Scenario (b) by the average duration (distance) of Scenario (a). The travel time ratio ranges from 1.11 to 1.30, with an average value of 1.17. For the travel distance ratio, the values vary from 0.62 to 0.82.

Table 4 Comparison of Scenario (a) and (b). Distance increases with respect to the beeline of 3 km, travel time ratio and travel distance ratio per district and overall (all).

	district							
	2	3	4	6	7	8	9	all
dist. incr. Sce.(a) [%]	93.65	102.14	86.39	90.08	123.63	138.11	131.42	108.72
dist. incr. Sce.(b) [%]	48.04	35.18	31.19	56.44	53.06	47.07	67.57	48.24
travel time ratio (b)/(a)	1.16	1.18	1.11	1.11	1.16	1.23	1.30	1.17
travel dist. ratio (b)/(a)	0.76	0.67	0.70	0.82	0.68	0.62	0.72	0.71

Table 5 Descriptive network properties for the public transport network surrounding the origins (averaged per district), for both the combined as well as for the individual networks. Station and line count are rounded to the nearest integer value.

	district						
	2	3	4	6	7	8	9
number of stations [#]	13	16	31	22	30	26	22
- bus	9	10	15	11	5	1	5
- tram	2	5	8	6	20	21	13
- subway	2	1	2	4	4	4	3
- train	1	1	6	1	1	0	1
service area coverage [%]	89.92	91.33	99.98	99.72	100.00	100.00	98.32
- bus	82.14	83.95	94.53	98.03	88.36	24.99	62.02
- tram	32.71	58.48	98.08	59.47	98.74	100.00	96.46
- subway	38.43	23.60	60.81	69.71	69.40	86.83	74.21
- train	18.64	21.30	57.26	11.77	12.25	0.00	20.28
avg. line direction diff. [°]	57.56	52.86	68.08	36.06	51.39	32.00	47.38
- bus	57.50	51.84	61.82	31.59	30.81	36.08	73.76
- tram	53.43	62.25	74.65	50.89	55.84	26.20	32.39
- subway	36.18	7.45	12.10	29.82	57.59	85.94	86.05
- train	51.71	89.84	89.84	nan	nan	nan	nan
network length [km]	6.06	8.34	18.40	8.85	9.28	8.60	9.41
- bus	2.69	4.06	6.61	3.81	1.59	0.34	1.71
- tram	1.08	1.97	3.61	1.91	5.28	6.33	4.41
- subway	1.33	0.72	1.49	2.95	2.26	1.93	2.32
- train	0.96	1.59	6.79	0.18	0.16	0.00	1.02
minimum walk duration [min]	2.31	2.89	1.80	2.57	1.52	1.78	2.76
- bus	2.99	3.11	2.11	3.02	4.38	6.67	4.46
- tram	4.35	5.32	3.39	4.71	1.83	1.78	3.18
- subway	5.85	6.16	5.73	6.34	5.58	4.10	5.57
- train	6.30	6.03	5.17	8.59	8.28	nan	7.31
number of lines [#]	9	9	9	10	13	11	12
- bus	7	6	3	5	3	1	4
- tram	2	3	4	4	9	8	7
- subway	1	1	1	1	2	2	1
- train	1	1	3	1	1	1	1

4.2 Public Transport Network Properties

As outlined previously, six different network properties are computed to describe the spatial characteristics of the public transport network in a 500 m neighbourhood surrounding each origin. The district-wise aggregated and averaged results are depicted in Table 5. The number of stations is lowest in the 2nd district with an average of 13 public transport stations per neighbourhood. The highest number can be seen in district 4 with 31 stations on average. The service area coverage shows full coverage (100.00%) for two of the seven districts (7 and 8), with district 2, 3, 4, 6 and 9 not being entirely covered (89.92%, 91.33%, 99.98%, 99.72% and 98.32%, respectively). Strong variations across districts can be seen for the average line direction difference, which ranges from 32.00° for district 8 to 68.08° for district 4. The average network length per neighbourhood varies between a minimum of 6.06 km (district 2) and a maximum of 18.40 km (district 4). The minimum walk duration is lowest for district 7 with an average of 1.52 minutes walk to the nearest public transport station and highest for district 3 (2.89 minutes). The average number of distinct lines is ranging from 9 lines (2nd and 3rd district) to a maximum of 13 lines in district 7. For the sake of completeness, Table 5 also outlines the properties per individual mode of transport, however, they will not be delineated in detail.

Table 6 Spearman correlation coefficients and p-values for the correlation between the network properties and the share of public transport of Scenario (a) and (b), for all public transport (PT) modes combined as well as for subway properties with the share of subway and tram properties with the share of tram.

Scenario (a)

	all PT modes		subway		tram	
	corr.coeff.	p-value	corr.coeff.	p-value	corr.coeff.	p-value
number of stations	0.048	.004	0.074	<.001	0.005	.784
service area coverage	-0.012	.474	0.069	<.001	0.040	.017
avg. line direction diff.	0.197	<.001	-0.415	<.001	0.043	.023
network length	0.101	<.001	0.260	<.001	0.013	.426
minimum walk duration	-0.053	.001	-0.100	<.001	-0.022	.229
number of lines	0.022	.189	-0.144	<.001	-0.010	.557

Scenario (b)

	all PT modes		subway		tram	
	corr.coeff.	p-value	corr.coeff.	p-value	corr.coeff.	p-value
number of stations	0.135	<.001	0.158	<.001	0.365	<.001
service area coverage	0.184	<.001	0.116	<.001	0.377	<.001
avg. line direction diff.	-0.143	<.001	-0.286	<.001	-0.259	<.001
network length	0.018	0.218	0.352	<.001	0.429	<.001
minimum walk duration	-0.254	<.001	-0.138	<.001	-0.188	<.001
number of lines	0.138	<.001	-0.102	<.001	0.312	<.001

Finally, for both scenarios, the Spearman correlation coefficients between network properties and public transport share are reported (see Table 6), together with the respective p-values. Starting with Scenario (a) - car, walk and public transport, no correlation is found between any of the combined public transport properties and the overall share of public transport (i.e. all correlation coefficients are below an absolute value of 0.25). However, for the correlation of the subway properties with the share of subway, a moderate negative correlation with the average line direction difference is reported (-0.415). Additionally, the network length shows a low correlation with the share of subway (0.260). For the tram modality, no correlation between any of the properties and the share of tram is found. For Scenario (b) - walk and public transport only, the combined public transport properties again do not have a noticeable relation with the share of public transport. But similar to Scenario (a), a closer look at the individual network level reveals significant details: The share of subway correlates with the length of the subway network (0.352). Furthermore, a negative correlation with the average line direction difference (-0.286) can be seen. In contrast to Scenario (a), also the share of tram shows a relation with the tram properties. The highest correlation coefficient is found for the network length (0.429), followed by the service area coverage (0.377), the number of stations (0.365) and the number of lines (0.312). Additionally, a low negative correlation is found for the average line direction difference (-0.259).

5 Discussion

In this section, the results shown in the previous section are discussed with respect to the research questions. The first subsection deals with the impact of cars on the modal split and how not owning a car affects the share of public transport across the seven origin districts for the fastest routes towards the centre. Second, the share of public transport and its differences across districts are related to the computed network properties. Finally, possible changes in the network are discussed that could increase the share of public transport for commutes.

RQ1: How does owning a car influence the modal split of time-optimised routes? When comparing the share of car across the different districts, it is notable, that cars are especially fast when starting from district 8 or 9. So a commuter living in those districts and wanting to reach the centre might not use the public transport options. This highlights the need for fast public transport in those areas, in order to influence the modal split in favour of public transport. In contrast, district 6 showcases good existing public transport, with more public transport than car. Hereby, most of the public transport share comes from the subway. This seems reasonable since there are two subway lines in the vicinity of district 6 leading towards the centre (compare Subfigure 1c). In fact, for most of the districts, the majority of the public transport share comes from the subway. Since the subway is a faster means of transport than trams or buses this seems valid. These findings are also confirmed by the results of Scenario (b), where the share of subway is predominant in almost all districts. Even though the subway has the highest share in absolute number, it is remarkable how much the tram gained when the car modality is removed. Overall, the share of tram increased from 1.30% to 23.14%. This raises the question of whether this growth could be promoted even more with changes in the tram network. Interestingly, district 9 has a high share of the fast modality subway and a relatively low share of walking, but still, it has the longest trip duration. This might be because of the trip length, which is also highest across all districts. It suggests, that a lot of detour is needed from district 9 to the centre (even though, this detour is mostly taken by subway).

Interesting results can be seen when comparing district 8 across the two scenarios. The share of public transport switches from the lowest share (when cars are allowed) to the highest share when excluding the car. This suggests that analysing public transport together with the car modality might lead to an inaccurate conclusion, namely that district 8 is not public transport friendly. However, as soon as the car is excluded, the results reveal the opposite with the highest share of public transport across all districts. This highlights the importance of this type of analysis, but further work is needed to fully understand these results.

When looking at the average trip duration, the differences between Scenario (a) and (b) are on average 3.6 minutes, with Scenario (a) being the faster option. So not having the possibility to go by car and thus using public transport takes about 15% longer. Expressed as travel time ratio it results in 1.17 (see Table 4). Values close to one suggest little difference between the two scenarios. The ratio found for Vienna is lower than what is found for São Paulo (2.2), Stockholm (2.0), Sydney (2.2), and Amsterdam (2.2) [23], suggesting a comparably good public transport for the analysed city. However, the cited study considers a much broader range of trip distances. For distances below 3 km, the authors report that public transport is faster than car use (ratio < 1), which is closer to the setup of our study.

On the other hand, the reported average trip distances are lower for walking and public transport only (Scenario (b)) and thus, also the increase in trip distance compared to the beeline is lower for all districts and the travel distance ratio is below 1. This suggests a more direct connection to the city centre by public transport rather than by car. Considering the layout of Vienna, this seems reasonable: The main roads are arranged in a circular manner around the city centre. In addition, some of them are one-way streets. Therefore, to reach a destination within the first district, one might have to take a long detour along these ring-shaped streets. Conversely, many public transport lines, especially subway lines, are oriented towards the centre and resemble a star-shaped layout (see Figure 1). Additionally, pedestrians have a dense network at their disposal, so fewer detours might be necessary for the walking portion of Scenario (b).

To summarise, having the car option for a commute to the city centre reduces the share of walking as well as the share of public transport on time-optimised routes. The results also suggest that the car is optimal to a different extent depending on the district of origin. In district 8 and 9, car is by far the fastest option to reach the centre. However, in district 6, public transport in its current state is already more attractive than the car modality with respect to fast routes. It is desirable to achieve this for all districts, as this could encourage commuters to shift to public transport. Regarding time-savings, owning a car has the highest impact for districts 8 and 9. Overall, the option of using a car reduces the average trip duration by about 3.6 minutes, however, the trip distance increases. These findings are strong incentives towards the use of public transport, as it takes only a little longer when refraining from travelling by car, and additionally, the travelled distance is shorter.

RQ2: How does the modal split of trips towards the city centre correlate with spatial network properties of the public transport network in the origin district? As outlined previously, the attractiveness of public transport varies for different districts of the city. This suggests that certain network properties could have an influence on the modal split of routes originating in different districts. The spatial characteristics included in this work only take the public transport network into account and, as a first result, no relation to the modal share is found in either of the two scenarios. However, these findings only apply to the properties of the combined public transport network. When investigating the properties of the subway and the tram network on its own, different relations become apparent. Network length and average line direction difference have an influence on the modal split. Additionally, also the number of stations, the service area coverage and the number of lines play a role to some extent. For all of them, the direction of the correlation agrees with the expectations.

In both scenarios, these network properties could explain, why district 8 stands out with a higher share of tram than subway. The network length has a positive impact on the share of the individual modes of transport and the tram network length is approximately three times longer than the subway network length in the 8th district (6.33 km vs. 1.93 km, respectively).

Similarly, the average line direction difference has a negative correlation and it is much lower for the tram network than for the subway network of district 8 (26.20° and 85.94°, respectively). A comparison with Figure 1 confirms that the only subway options in the vicinity of district 8 connect north to south rather than to the centre. These characteristics might make the subway less optimal for reaching the first district in a time-efficient manner and the routing algorithm therefore tends to opt for tram.

More generally, the results of the correlation analysis suggest that public transport should not be considered as one network but rather analysed on the level of individual modes of transport. This allows a better understanding of the differences across districts and why particular modes of transport are chosen for different districts.

RQ3: Can we identify factors in the public transit network that hold the potential to increase the share of public transport? To increase the modal split in favour of public transport, the proposed measures are a good starting point to identify potential changes. However, the points highlighted in the previous section suggest, that not one single measure is of importance, but rather a combination of several ones. If additional lines would be introduced, they should preferably cover areas where little public transport is present so far. Furthermore, they should be oriented in a way to connect important regions in a city. These regions do not necessarily need to be the city centre, but they can be defined according to interest, be it residential areas, parks, education centres, etc. The results also suggest, that even though the bus network is rather dense with a high number of stations and lines, plenty of network length and a good service area coverage, they do not play a role in time-efficient routing. This leads to the assumption that buses are a slow means of transport. Of course, it should not be neglected that buses have some important advantages compared to other means of transport, with the biggest one being that no tracks are needed whenever a new line is introduced.

To increase the share of public transport for the city of the present case study, special focus should be given to district 8 and 9, where currently the car share is above 87%. This suggests that there are few fast public transport options. The high percentage of car use could be a result of the districts being located closer to time-efficient highways. However, further work is needed, to incorporate not only the characteristics of public transport but also the characteristics of the street network.

6 Conclusion

In this work, we present an algorithmic approach to investigate the share of public transport on commute trips towards the city centre of Vienna. Two different scenarios are applied, to analyse time-optimised trips with varying modal options included in the underlying multi-graph. For Scenario (a), car, walk and four public transport modes are part of the multi-graph, whereas for Scenario (b) the car modality is removed, so only walking or public transport can be used to reach the destination. The trip origins are distributed among the seven neighbouring districts of the centre, with a total of 3500 trips (500 starting in each district). This allows a comparison across the district as well as an investigation of how owning a car influences the modal split of time-optimised routes. The results highlight one district where the existing public transport outperforms the car option, as well as two other districts where the car modality takes up only about half of the share. However, two districts in particular are identified, where investments should be made in public transport, with a current share of car of more than 87%.

The second part of the work is focused on public transport network properties and whether they have an impact on the percentage of public transport in the modal split. Six network metrics are computed for the surroundings of the route origins. Among them, the network length and the average line direction difference are found to have an influence on the modal split of subway and tram. However, it should be noted, that more targeted measures need to be identified in order to explain the differences shown in the result section.

Finally, there are some limitations that need to be addressed. The case study considers only the inner districts of Vienna, which limits the analysis and the findings to the central parts of the city. Since the outskirts of the city make up a large part of the urban area, they should be considered in future work. This might add deeper insights into the impacts of the car modality and the interplay with public transport options on the level of the whole city. Additionally, one might argue that excluding the bike as a modal option is not appropriate, since it is an important modal choice. Future work should find a meaningful way to incorporate the bike option in this sort of analysis, maybe through an additional scenario where both walking and biking are analysed in a combined way as active means of transport. To create a more complex multi-graph, also taxis and/or shared means of transport could be included in future work. Since car sharing has become increasingly popular in recent years, it could allow further insight into the modal choices within an urban area, without just focusing on private cars. Lastly, the current approach models the best-case scenario without taking the impact of traffic and congestion into account. In future work, the car speed could be modified (i.e. decreased) to model peak times during the day. Additionally, the current multi-graph includes public transport in its average form, with mean waiting time and constant frequency. Including precise timetable information would be a reasonable next step, allowing a dynamic analysis of the modal options throughout the day. This way, peak and off times could be compared and much deeper insight into travel behaviour could be gained.

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