Optimizing Transport Network to Reduce Municipality Mobility Budget

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Abstract: Mobility budgets dictate the limit of CO_2 per capita, which is calculated based on the mode of travel and distance. Mobility budgets are one of the final goals of the optimisation of transportation network, when the aspects of fairness and equity are considered. The main problem arises when we focus on multiple criteria of fairness and equity. In addition, it was observed that any drastic change in behaviour leads to inadequate initial parametrisation, especially under the effects of COVID-19. This can also mean that optimising transportation network according to class-to-be is most likely to cause behaviour changes in relation to the use of public transport. The aim of this article is to define the structure of optimisation task, based on mobility budget provided on a monthly basis. This research was based on public transportation data and mobile activity data. The former was used to determine the usage of public transport during 2017 and 2022, while the latter provided enough information to determine exactly how COVID-19 affected the behaviour of city districts and provide concrete information regarding necessary re-planning measures for public transportation station locations. In result, the optimisation solution was proposed by defining case-specific objective functions and constraints.

1 INTRODUCTION

In the contrast of advantages brought by economic growth, the increase in overall Greenhouse Gas emissions (GHGE) (International Energy Agency, 2022) raises an issue of balancing the use of technological operations versus their environmental cost. It includes almost all fields – from industrial operations like food production (Boke Olén et al., 2021) and waste utilisation (Yasmin et al., 2022) to personal carbon footprint (Khanam et al., 2022).

In order to address GHGE, European Commission of European Union (EU) adopted a series of proposals with the main goal of achieving climate-resilient society (European Comission, 2020). The results of developing technologies and strategies aligning with these proposals can already be seen with reduction of overall GHGE in EU from 2019 to 2020 by 0.37 Gt (European Environment Agency, 2021). While it seems positive, during these years the COVID-19 pandemic was most active. As a result, based on global CO_2 emissions (International Energy Agency, 2022) the reduction in 2020 may be a pandemic's post-effect dip that returned even higher in 2021.

It was found that the COVID-19 pandemic did indeed have negative impact on CO_2 emissions

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(Jawadi et al., 2022; Kareinen et al., 2022; Nicolini et al., 2022). This relates, for example, to the enforcement of homestay, including remote work, and reduction of leisure group sizes at early stages of the pandemic until now when improved protection measures are in place. The adoption of these principles, including people wish for less exposure to public places, led to population behaviour changes – more people switched from public transport (PT) to personal transport for commute (Delbosc et al., 2022), as the latter proved to be a safer and less restrictive mode of travel during COVID-19 (Zafri et al., 2022). This, in turn, resulted in an increase of personal carbon footprint in mobility, and the term "rebound effect" was introduced (Rojas et al., 2022). As Jawadi et al. (Jawadi et al., 2022) point out, short-term strategies have no significant contributing effect and sustainable long-term solutions should be developed instead. This includes changing the way of perception of daily carbon footprint (Hoffmann et al., 2022).

Carbon footprint can be related to multiple activities and fields, while most prominent in the effect on CO_2 during and after COVID-19 was transportation (Li et al., 2021; Vélez, 2022). There can be various approaches to manage carbon footprint. In general, carbon footprint management is implemented by applying carbon budgets to regions, countries and industries. Although the debates on fairness of allocation of these budgets is still ongoing (Pan et al., 2022; Williges et al., 2022), the common consensus is that equity must be supported (Hänsel et al., 2022). In this instance, equity refers to the relative distribution of benefits and costs. Therefore, while it is possible to manage carbon footprint on national and industry levels by applying government regulations to stakeholders (Bocken & Allwood, 2012), the individual carbon footprint management cannot be forced (Khanam et al., 2022).

Individual carbon footprint includes mostly choices of food, both its production and initialization, technologies and modes of mobility. Researchers suggest that the mode of mobility leaves the largest impact on the carbon footprint per capita (Bhoyar et al., 2014; Li et al., 2021). Application of mobility budgets offers a more specific approach to travel-related carbon footprint management. Following the main aspect of localised carbon footprint management, the mobility budgets are calculated and specified according to region, objective and target groups.

There are various ways to approach specification of mobility budgets. For example, in study of carbon footprint in college mobility the basis was put on survey data and existing local policies in order define multimodal logit model that shaped optimal combination of mobility modes (Crotti et al., 2022). Another study (Sánchez-Barroso et al., 2022) was using surveys to acquire data on mobility modes of people traveling to healthcare centres. This data was then used to estimate GHG emissions and it was found that managing the mobility modes does lead to reduction of GHG emissions.

In essence, mobility budgets dictate the limit of CO_2 per capita on daily/weekly/monthly basis. The level of CO_2 is thus calculated based on the mode of travel and distance. Currently, there are no standardized characteristics of an individual mobility budget, even though multiple attempts have been made to define them. Focusing on multiple aspects of fairness and equity raises the main challenges. These aspects include Millonig et al. (Millonig et al., 2022) hypothesised variants to characterise mobility budgets based on average ceiling values such as daily distance travelled by a particular mobility mode and specified mobility budget for Austria.

The conclusion suggests that even though it is possible to put limits on mobility budgets, it is strictly region-based and requires in-depth analysis of the given region's socio-geographic needs which makes one-size-fits all approach impossible even in EU Mobility budgets are not always the final goal of transportation network optimization, however, many such tasks are based on criteria of fairness and equity (Caggiani et al., 2017; Lucas et al., 2019). In addition, the fairness in terms of transportation policies is not yet clearly defined (Randal et al., 2020).

The problem of designing an optimised transportation system is not novel, but it has attracted more attention in recent years (Caggiani et al., 2017). Farahani et al. (Farahani et al., 2013) provided a sophisticated review on transportation network design problems almost a decade ago and concluded that a lot of work will be required in the future to address questions such as objective functions and constraints, correct decision-making strategies and multi-modality of networks. Later, an overview of multilayer network designs was provided (Crainic et al., 2022) by applying own classification methodology with the focus on taxonomy. There are various approaches to optimising a transportation system.

Gu et al. (Gu et al., 2018) used simulation-based optimization to propose toll pricings that would result in maximised network density. The last decade also showed a switch of research and application focus towards multi-objective optimization (MOOP) in various fields (Al-Ashhab, 2022; Ogumerem et al., 2018; Sun et al., 2014).

Zhang et al. (Zhang et al., 2022) proposed a network design based on hidden Markov model and an Equilibrium Optimizer to solve a MOOP. Authors used information about passenger paths, amount and duration of trips to optimize public transportation aspects – minimising costs and maximising the number of trips. The work shows good results compared to algorithm such as Floyd-Warshall.

Wang et al. (Wang et al., 2020) proposed a model based on Non-dominated Sorting Genetic Algorithm II to solve MOOP of customizing bus routes in real-time. The model aimed at achieving two goals – to minimise travel time and minimise total operating costs. Authors used information about the travel time, including boarding times and total travel time, and the conditions of bus stations such as station's accessibility, total demand and the availability of parking lots. The authors used demand data obtained from local citizens. It means that particular objective functions and constraints may vary depending on transportation network and, therefore, they must be defined as case-specific.

MOOP involves multiple objective functions that are to be minimised or maximised. Compared to single-objective optimisation problem, the best solution cannot be determined by comparing values of objective functions; instead, dominance must be used as a goodness value. For example, an angle-based constrained dominance principle (Fan et al., 2019). The answer of MOOP is a set of solutions that define the best trade-off between competing objectives subjected to constraints. These constraints are often defined by case-specific boundaries.

Considering the mobility budget as a goal for MOOP, the objective functions should address fairness and equity principles of travel – accessibility, mobility, variety of types of transport, social equity, while constraints should address both mobility aspects and GHGE in general. The result of this MOOP is a mobility budget provided on a monthly basis.

Therefore, the aim of this article is to define the structure of optimization task address fairness and equity principles of travel, based on mobility budget provided on a monthly basis.

The remainder of this paper is organised as follows. The next section describes procedures for data gathering and analysis. Afterwards, the results of public bus service data and mobile network data analysis are presented. Finally, the aspect of mobility fairness is chosen and objective functions criteria for the optimisation task are selected.

2 METHODOLOGY

As it was already mentioned, COVID-19 had a negative impact on overall CO_2 emissions. In order to determine particular MOOP parameters, the data gathered was analysed in consideration of the said impact. The choice of MOOP objective functions and constraints was a prerequisite for determining parameters of PT and selecting those affecting mobility budgets.

Four types of data were considered: general data, PT data, monitoring data and mobile activity data. Aspects of transportation data can be defined as follows:

- A trip is any movement (>100m) originating from a location where the resident has an activity to a destination where the resident has another activity;
- Destination may be any public place;
- The trip is over when the destination is reached;
- The trip may be followed by another trip (movement) to another destination.

2.1 General and Public Transportation Data

This data includes the following parameters for all types of transport:

- Average trip distance (km) per resident per day;
- Average trip time (min) per day;
- Average and maximum moving speed (km/h);
- Total number and types of roads available for PT, private vehicles and trucks per day;
- Total number and types of vehicles in the city per day.

Average trip distance and trip duration dictate the general need for transportation (both public and private) including the number of PT vehicles, number and location of stations. Statistical data around these parameters can be used to determine commute routes in order to develop transportation hubs. Moving speed determines the distance of travel, especially during commute hours.

Total number and types of available roads allow calculation of optimal routes for trucks, including city bypass routes (for example, city of Jelgava in Latvia has a regulation forbidding large trucks to pass through city centre). Additionally, it serves as a data source for PT route planning as it defines actual road capacity, i.e., the maximum number of vehicles per day.

Total number and types of vehicles in the city allow calculating the distribution between private, freight and PT vehicles, and it can be used as one of the parameters in multi-criteria optimisation. PT data includes the following parameters that relate to public service vehicles such as busses and trains:

- Total number of PT vehicles on duty per day;
- Total number of transportation routes;
- Average fullness (%) of each PT vehicle per route;
- Total number of trips per region;
- Most active period of the day (h);
- Ticket price;
- Fuel price;
- Use of multi-modal PT routes.

Total number of PT vehicles on duty and corresponding total number of transportation routes shows the usage of PT versus private vehicles. Average fullness is one of parameters for calculating effectiveness of transportation system. Total number of trips determine the need to either increase or reduce the number or PT vehicles depending on fullness statistics.

The most active period of the day, or several such periods, define the required amount of stations and frequency of PT lines. The ticket price versus fuel price (including use of private vehicles) shows how attractive PT is to residents compared to other travel options. Multi-modal PT routes defined by the number of different types of PT vehicles used for one trip provide necessary information to determine if improvements to an existing route are required and/or a new PT route is needed and/or change towards hub-type mobility model must be considered.

2.2 Monitoring Data

This data includes the following parameters relating to observatory data that can serve as supportive information:

- Number of vehicles entering and exiting the city;
- Moving speed of vehicles within city limits;
- Parking violations;
- Environmental data.

This type of data is typically provided by monitoring devices embedded in urban infrastructure: video cameras, speed sensors, meteorological stations, etc. Cameras may be used at city entrances in order to register vehicles entering and exiting the city in order to determine internal city traffic and improve or add/remove existing entry/exit routes. Speed sensors embedded in road surface determine the moving speed of vehicles in order to optimise the traffic flow (including road capacity and traffic flow intensity). Parking violations can decrease road capacity, thus breaking the optimised traffic flow.

Finally, the environmental parameters such as air temperature, wind direction, wind speed, humidity and rain/snow precipitations can affect traffic conditions, resulting in the need to adjust traffic flow (for example, changing the traffic light algorithm in real-time).

2.3 Mobile Activity and Data Acquisition

This data includes the following parameters that depict mobile activity, including the location and movement, of residents:

- Mobile call density in a territory;
- Mobile user density in a territory;
- Mobile internet usage in a territory;
- Mapping of mobile base stations within a municipal territory;
- GPS coordinates for mobile base stations;
- Spatial grid of 1km x 1km size;
- Mapping of mobile base stations in the spatial grid of 1km x 1km size.

In general, this data should be used together with other types of data in order to determine such aspects as the proximity of residents' commute route to PT stations, the type of district based on commute hours, i.e., business or dwelling area. Based on the availability of data, including communication and legal agreements with local municipality, traffic authorities, PT companies and telecommunication companies, two types of data were selected – PT data and mobile activity data. The data was gathered in Jelgava City, Latvia.

Based on the legal agreement between Latvia University of Life Sciences and Technologies and Jelgava City Municipality, PT data was provided by Jelgavas Autobusu Parks Ltd, the main PT service operator in Jelgava. The provided data cover two comparable periods – February 2017 and February 2022, to demonstrate the effect of COVID-19 restrictions on the use of PT vehicles. The following data was provided:

- Number of entries and exits from a PT vehicle at a particular bus stop, % of total number;
- Difference between entries and exits at a particular bus stop, *n* count;
- Distance travelled per trip and per day, *km*;

- Distance travelled depending on passenger category, % and *n* count;
- Duration of travel per trip and per day, *min*;
- Average duration of travel per week, *min*.

Mobile activity data was provided by the telecommunication company, Latvijas Mobilais Telefons Ltd (LMT). Mobile activity data was selected for the same periods as for the PT data. The data acquired was call data records that is a by-product resulting from mobile operator network events in Jelgava, Latvia. The location of particular subscribers at the start of the phone call was determined by the nearest mobile base station. Each station is an infrastructure object that ensures mobile connectivity. In addition, this data was consolidated with 15-minute steps; therefore, identification of movement of specific persons was not possible. In addition, it was impossible to identify specific persons; therefore, the privacy aspect was not an issue that would require additional regulations. The obtained data includes:

- The number of unique subscribers in Jelgava (for years 2017 and 2022), *n* count;
- The number of unique subscribers per station per day of the week and per hour of the day, *n* count.

Analysis of data was performed using RStudio (Posit, PBC, version 2022.02.0) and Python (Python Software Foundation, version 3.10.4).

3 RESULTS

As it was previously mentioned, in order to get a statistical impact of COVID-19 on PT vehicle use, the data from February 2017 and February 2022 were compared. On average, there were 2.24 times more trips on weekdays in February 2017 than in February 2022. This shows a significant difference between the number of trips on weekdays and holidays. In comparison, there were 2.03 times more trips on weekdays than on weekends in 2022.

At the same time, due to the COVID-19 restriction measures, the total number of trips in 2022 decreased by 62.9% compared to 2017, but the general tendency between weekdays and weekends remained the same. The distance travelled per single passenger trip was calculated (see Table 1).

The results show that the distance travelled does not differ significantly between weekdays and weekends. The average distance travelled was 4.61 km per passenger trip in February 2017 (see Figure 1).

Table 1: The distance travelled (km) per single passenger trip in February 2017.

Day	Mean	Median	Std. Deviation	Number of trips
Weekend day	4.63	3.90	2.67	32 724
Weekday	4.61	3.83	2.67	183 139
Total	4.61	3.85	2.67	215 863

Similarly, the distance travelled per single passenger trip was calculated for February 2022. The results show that the travelled distance does not differ significantly between weekdays and weekend days – the average distance was 4.73 km per passenger trip in February 2022 (see Table 2).

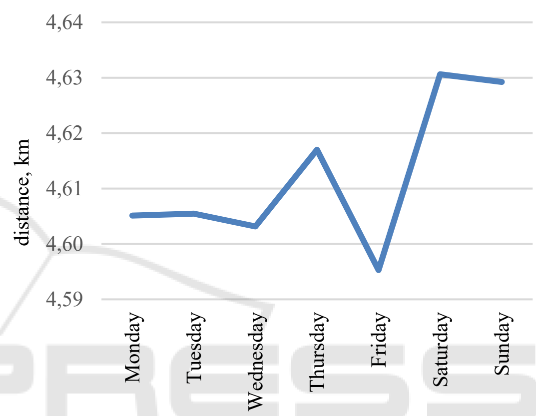

Figure 1: Average distance travelled (km) per single passenger trip in February 2017.

In 2017 and 2022, the average observed trip duration was up to 13 minutes and no significant differences between years regarding trip duration was observed. In addition, trip duration did not differ significantly between weekdays and weekends. The same tendencies with average distance travelled per trip per weekday were observed for 2022.

Table 2: The distance travelled (km) per single passenger trip in February 2022.

Day	Mean	Median	Std. Deviation	Number of trips
Weekend day	4.68	4.06	2.62	13 218
Weekday	4.74	4.12	2.68	67 052
Total	4.73	4.10	2.68	80 270

However, the behaviour patterns affected by COVID-19 show significant changes – in 2022, the travel distance decreased on weekends, while in 2017, the travel distance increased on weekends (see Figure 2).

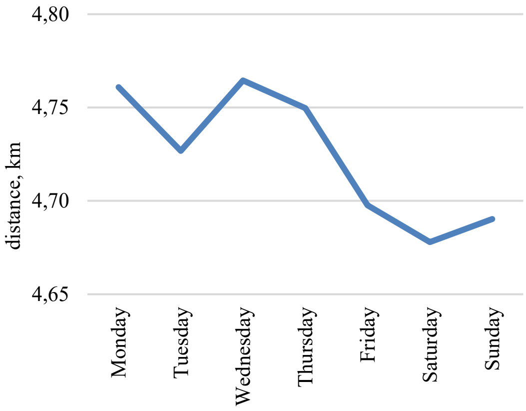

Figure 2: Average distance travelled (km) per single passenger trip in February 2022.

Due to the introduced COVID-19 restriction measures, an overall decrease in the number of residents travelling by PT was expected. Analysis of passenger turnover was performed, and it was found that the turnover in February 2022 was 2.6 times lower than in February 2017.

3.1 Mobile Activity Data Analysis

Mobile activity data was analysed using Principal Component Analysis (PCA) with an aim to categorise districts based on their economic activity. PCA was selected to generate complex factors that have linear correlation with original features, i.e., unique subscribers per base station during a day and time.

As a result, two complex factors that describe 94.9% of overall data variability PC1 (65.2%) and PC2 (29.7%) were obtained. The average values of PCs were calculated based on weekdays in February 2017. It was concluded that PC1 has higher values on Fridays and Sundays and lower values on other days. Therefore, it hypothesised that the city districts included in PC1 are residential districts, but those in PC2 - business districts.

Upon analysing individual base stations, it was concluded that three types of districts could be distinguished – business, residential and mixed districts. However, only one base station (Liela iela 2) belonged to a business district – others were categorised as either mixed or residential types.

Similarly, the average values of PC1 and PC2 were calculated based on the time of the day (in hours). On weekdays, PC1 had lower values between 00:00 and 15:00 and higher values after working hours (15:00-22:00), while PC2 had higher values between 00:00 and 15:00. Therefore, the previously stated hypothesis that PC1 referred to residential districts, but PC2 – to business districts is valid.

Based on these results and data on the total number of subscribers per base station, there were three groups of districts in February 2017 (see Figure 3). Only one base station (Liela iela 2) referred to a business district category.

Analysis of data for February 2022 lead to the conclusion that the overall division of districts have changed due to COVID-19 restrictions, causing increase of remote work from home. Using PCA, two complex factors that describe 95.7% of overall data variability PC1 (51.0%) and PC2 (44.7%) were obtained.

Instead of falling into strict categories of residential or business type districts, every district is now considered as partly "mixed". Therefore, two groups of districts may be distinguished – mixed business districts and mixed residential districts.

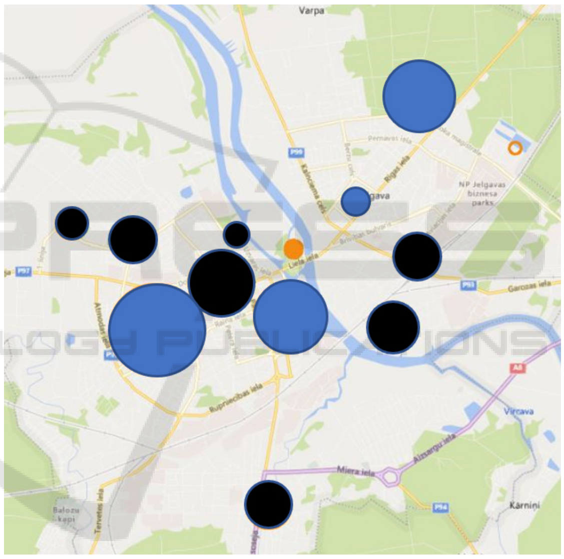

Figure 3: Base station classification based on district type: blue=residential districts, black=mixed districts, orange= business districts, February 2017.

For example, the only business district of 2017 became one of the multiple mixed business districts in 2022 (see Figure 4). Overall, these results show that initial classification of districts as a parameter for determining point of interest (POI) for further planning of mobility budget may vary depending on situation.

Optimisation of PT network in order to assess and assign a correct mobility budget to each resident is based on the notion of appropriately selected optimisation criteria. Analysis of bus network

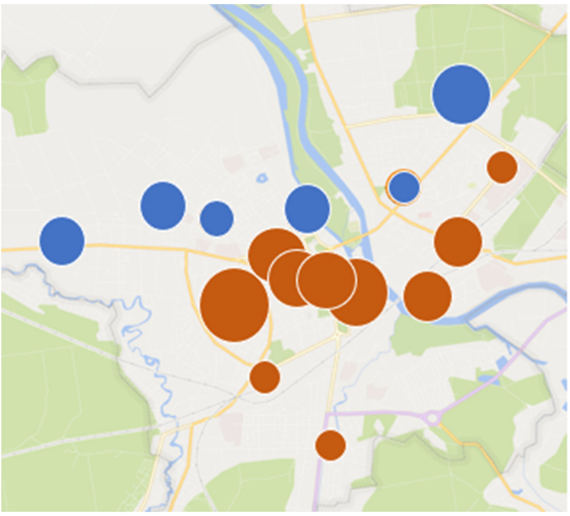

Figure 4: Base station classification based on district type: blue=mixed residential districts, orange=mixed business districts, February 2022.

operations and mobility activity data in Jelgava provided the basis for understanding what exactly is required to define such criteria.

3.2 Optimization Criteria for Public Transportation Network

The primary goal of optimisation is to find a solution that meets the needs of passengers in terms of fairness, including the choice of PT vehicle as type of transport, availability of such PT vehicles on the city roads and accessibility to PT vehicle stops. Addition of mobility budget on top of passenger needs results in a requirement to find a solution for optimal PT vehicle trip described by appropriate route in relation to district classification.

The optimisation problem solutions are defined as a mobility budget provided on a monthly basis as:

- Decision space in which the individual person can choose from different options to cut down emissions and stay within the limit;
- Indicator for authorities and transport providers where improvements in accessibility and transport options are needed to “unburden” narrow budgets.

Therefore, the objective for optimising the transportation network in Jelgava, Latvia, can be defined as follows:

- Minimise the travel distance required to access the point of interest when using single type of transportation, i.e., a bus.
- Minimise travel duration to access the point of interest when using multiple types of transportation or multiple PT vehicles for a single trip.

The objective functions are subjected to multiple defined constraints:

- Decarbonisation of a specific region (e.g. a city), for example, reduction by 10% compared to the previous year, divided among all residents;
- Local circumstances: accessibility and availability of alternatives;
- Social circumstances: supply and care obligations, financial situation;
- Basic functions of living: work, education, daily needs;
- Constants of human mobility, e.g. the travel time budget (60-90 minutes per day, regardless of the means of transport or location), and 3-4 trips per day;
- Trading option for a limited part of the emission allowances per capita (e.g. 10%).

4 CONCLUSIONS

Published research suggest that the mode of travel leaves the largest impact on the carbon footprint per capita. Analysis of people behaviour also show that personal vehicles were preferred mode of mobility during COVID-19 pandemic.

Data analysis suggests also that the behavioural changes caused by the initial enforcement and later encouragement of COVID-19 restriction measures led to rapid decrease in the use of PT vehicles. In February 2022, the total number of passenger trips had decreased by 62.9% compared to February 2017, leading to a dramatic decrease of overall passenger turnover.

It is interesting, however, that the intensity of PT vehicle uses on various days of the week did not change much – in February 2017, there were 2.24 times more passenger trips on weekdays than on weekends, but in February 2022, the same parameter was 2.03 times more trips on weekdays compared to weekends.

At the same time, the observed travel time and total duration per passenger did not decrease, and remained at about 13 minutes for both periods. Multiple researchers found similar situations in their countries (Chang et al., 2021; Delbosc et al., 2022; Shaer & Haghshenas, 2021; Sogbe, 2021).

It is important to mention that except of analysing general transportation statistics, no data relating to equity principles (Lucas et al., 2019) was observed. This would include segregation into genders, age (for example, more detailed than just "children"), ethnicity and overall ability of movement. Even though these parameters play a significant role in optimisation and mobility budget assignments, no PT service company would gather such data.

Regarding the classification of mobile phone base stations, it was observed that any drastic change in behaviour leads to inadequate initial parametrisation. This can also mean that optimisation of transportation network according to class-to-be is most likely to cause behaviour changes regarding the use of PT vehicles.

However, mobile activity data reveal enough information to determine exactly how COVID-19 affected the behaviour of city districts and provide concrete information about the necessary re-planning measures for PT station locations.

As the modes of mobility even after the COVID-19 pandemic shifted more to use private vehicles, particularly cars, government institutions may need to initiate switch from extensive use of private vehicles to public vehicles or private vehicles which produce less CO2. This could be done through campaigns, providing optimized PT routes and times, offering free tickets and other ways. Thus balancing, for example, between reaching decarbonisation goals and providing sustainable PT network which is used by citizens.

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