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Dynamic demand patterns in the profit optimisation of bike-sharing station locations: an agent-based analysis of the greater Vienna region

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ABSTRACT
This study employs the MATSim agent-based simulation model to analyse bike-sharing station locations by examining dynamic trip flows and individual behavioural changes. It explores demand on a microscopic scale, capturing the behaviour of multi-segment trips. A protocol was established to evaluate different station configurations' impact on profitability and demand. Findings suggest that optimising the station count from 219 to 66 strategic locations can significantly enhance both revenue and operational efficiency. The simulation produces data on the number of users arriving and departing from each station in different configurations, indicating the size of each station. This data allows stations to be classified into three types: generator, attractor, and interchange; displaying their changes across different configurations. This quantification offers operators insights for predicting bike distribution and planning operational strategies. Considering spatial and built environment factors, the findings underscore the potential of bike-sharing stations to evolve into mobility hubs, offering valuable insights for policymakers.

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Bike-sharing station; location; agent-based model; MATSim; optimisation

Introduction

The increasing adoption of shared micromobility modes in various countries has prompted local governments to prioritise the provision of comprehensive facilities. The aim is to establish micromobility as a viable alternative for -first-mile-last mile journeys, thereby improving the quality of existing trips and generating new trips. Incorporating shared modes into the existing transportation network is considered a crucial step in achieving this objective (Shaheen and Chan 2016). This integration can also be viewed

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as an initial step in allocating a mobility hub in a location associated with the usage of different mobility options (Duran-Rodas 2022).

One of the earliest and widely adopted shared transportation modes is bike-sharing (BS). As of December 2022, bike-sharing systems (BSS) are operational in 1,590 cities across 92 countries, with 35% of them categorised as dock-based systems (Meddin and DeMaio 2021). In a system with a significant number of docking stations, demand forecasting and substantial resources such as inventory decision-making and rebalancing (Gammelli et al. 2022; Yin et al. 2023) are required to maintain all stations and quickly recover them. Determining BS stations is one of the most complex tasks in the BSS planning process (National Association of City Transportation Officials 2016). Consequently, optimal BSS placement is essential (Zhang et al. 2022) and optimising their distribution across the service area (Neumann-Saavedra, Mattfeld, and Hewitt 2021; Rennie et al. 2023).

The use of BS stations depends on the entire day's travel context, where the value of a trip extends beyond the journey itself. In this context, the utility of a trip arises not only from the trip's inherent attributes but also from its role in facilitating access to activity locations throughout the day. Existing studies on BS stations often begin with traditional location-allocation problems, depicting users as static entities and typically derived from aggregated population or usage record data (Fazio et al. 2021a; Guler and Yomralioglu 2021; Jin, Nieto, and Lu 2020; Mix, Hurtubia, and Raveau 2022). The term 'static' refers to the lack of consideration for the changing interactions between users and locations and how these dynamics affect users' choice of station locations. Aggregate data inadequately reflects the subtle behaviours of travellers and their reactions to transportation systems, underscoring the need for more complex simulations like agent-based models to capture these dynamics (Kagho, Balac, and Axhausen 2020).

In examining the context of Vienna, the widespread distribution of BS stations stands out as a notable feature. Despite boasting an extensive public transport network covering almost all areas, Vienna still records a relatively high proportion of private car trips, reaching 25% in 2019. Meanwhile, public transport, walking and cycling constitute 38%, 30% and 7%, respectively (Mobilitätsagentur Wien GmBH 2019). Vienna has set ambitious targets to increase the share of eco-friendly modes, including shared mobility options, to 80% by 2030 and well over 85% by 2050 (Smart City Strategy Vienna 2022). To achieve these goals, the city has strategically placed over 200 BS stations with 3,000 bikes to facilitate multimodal travel. Furthermore, Vienna has introduced prototype mobility hubs offering diverse shared modes such as e-cars, e-scooters, cargo bikes, and bike-sharing, aiming to address various sustainability objectives (Duran-Rodas et al. 2023).

Integrating a significant number of BS stations into the overall public transport system offers considerable advantages. However, factors such as usage per station and the total number of stations play a crucial role in determining the profitability of BSS investments. This study employs an agent-based simulation model to characterise station locations, considering dynamic trip flows resulting from individual behavioural changes. The model aims to enhance planning and decision-making for the optimal placement of BS stations. Using Vienna, Austria, as a case study, the paper illustrates how the simulation model adeptly captures the dynamic interaction among the number of stations, their locations, BS demand, and profit optimisation planning. The paper is structured as follows: Section 2 provides a literature review, Section 3 outlines the research methodology, Section 4 presents the simulation results, and Section 5 discusses the findings. Finally, Section 6 concludes the paper with implications for future research.

Literature review

Facility location has been extensively studied in the field of operations research. This field focuses on determining the most suitable locations for factories, warehouses, and service facilities while complying with various constraints to meet specific business objectives. Such models aim to minimise the number of facilities required to serve customers efficiently or to identify the most promising or optimal locations (Lee 2023). In establishing multiple new facilities, it is important to consider the allocation of demands to facilities (Daskin 2013) and the interaction between facilities based on their distances (Karakitsiou 2015). In the broader context of location and allocation models, location problems can be categorised into three distinct methods, namely continuous, network, and discrete models, with differences arising from the assumptions made about spatial demand and location points distribution in space (Daskin 2013).

Early BS station location studies begin with establishing the spatial representation of demand points and station locations, followed by identifying the most optimal station locations based on various objectives and constraints. The majority of location-allocation studies assume demand as discrete points (Frade and Ribeiro 2015; García-Palomares, Gutiérrez, and Latorre 2012) and network data (Caggiani, Colovic, and Ottomanelli 2020; Jin, Nieto, and Lu 2020; Lin, Lin, and Feng 2018). The diversity in assumptions results in various approaches to representing demand points, which significantly affects the precision of outcomes in determining the optimal locations for BS stations.

Researchers commonly employ at least two data sources to represent demand points when modelling optimal BS station locations: (i) big data sources, and (ii) demographic data. A data-mining approach was employed by (C Park and Sohn 2017), who used hourly floating population data from mobile phone signal locations and considered attraction sites to estimate demand points. This data was then combined with taxi trajectory pick-up locations as a proxy for estimating potential locations for BS stations. GPS data from BS users, along with real-time occupancy per station, was utilised by (Mix, Hurtubia, and Raveau 2022; Soriguera, Casado, and Jiménez 2018), while (Banerjee et al. 2020) augmented with sociodemographic user data to estimate demand point locations and road usage intensity. The use of big data for BS usage and travel frequency, combined with population-based aggregate demand per traffic zone, was applied by (Dehdari Ebrahimi et al. 2022) for the same purpose of representing demand points.

An alternative approach is to represent the demand for BS by leveraging population data based on traffic zones. This data is simplified into aggregate data per zone or small grids, as utilised by (García-Palomares, Gutiérrez, and Latorre 2012), who combined aggregate population data with employment rates associated with building data and the number of trips generated and attracted per traffic zone. This data processing yields a representation of the demand distribution for BS users. (Frade and Ribeiro 2015) estimated the potential demand for BS based on the target public, users' trips, and the physical characteristics of the hilly city of Coimbra. (Lin, Lin, and Feng 2018) generated trips from the population in 32 blocks of the study location using ratios from previous studies, while Conrow, Murray, and Fischer (2018) used a traffic zone-based population representation and bicycle usage ratios to measure bicycle demand intensity. Differing from most, (Yuan et al. 2019) treated demand as an output of the model based on 15 simulated scenarios. 70 BSS station locations were determined based on criteria related to proximity to attraction sites and the public transport network within a study area.

Following the representation of demand points, the next step involves mapping these points to potential BS station locations using specific attraction functions. (García-Palomares, Gutiérrez, and Latorre 2012) employed a station usefulness formula that considers the availability of opportunities near the intended station locations. (Banerjee et al. 2020) applied a bike station suitability score to predefine station locations, while (R Mix, Hurtubia, and Raveau 2022) utilised an accessibility function to generate a spatial distribution of trips from BS transaction records. In this process, the impedance cut-off value between demand points and station locations is arbitrarily set. Short distances ranging from 100 to 300 meters were used by Dehdari Ebrahimi et al. (2022), Juan Carlos García-Palomares, Gutiérrez, and Latorre (2012) Jian Gang Jin, Nieto, and Lu (2020); Park and Sohn (2017) whereas (Banerjee et al. 2020) incorporated an additional calculation for an impedance cut-off distance of 1000 meters to maximise the location's market share.

The final phase in studies on BS station location involves the optimisation of station placements. A commonly used method is the location-allocation model, specifically the maximise coverage model, as evidenced by the works of Dehdari Ebrahimi et al. (2022), Frade and Ribeiro (2015), J. C. García-Palomares, Gutiérrez, and Latorre (2012), Lin, Lin, and Feng (2018), R. Mix, Hurtubia, and Raveau (2022), C. Park and Sohn (2017). This model considers various factors such as budget constraints (Frade and Ribeiro 2015), efforts to minimise cyclist risk and maximise comfort, and the aim to reduce negative impacts on traffic from rental stations and bikeways (Lin, Lin, and Feng 2018), as well as to minimise the number of stations (Dehdari Ebrahimi et al. 2022). The P-median problem is also frequently employed (García-Palomares, Gutiérrez, and Latorre 2012; Chung Park and Sohn 2017) as an adjunct to the maximise coverage model. Other popular methods include GIS-based approaches (Fazio et al. 2021b) and their integration with multiple-criteria decision analysis techniques such as AHP, Fuzzy AHP, and the Best-Worst method (Eren and Katanalp 2022; Guler and Yomralioglu 2021). Mathematical programming approaches are also widely used, including Mixed Integer Linear Programming (Yuan et al. 2019) with variations such as the two-stage stochastic model (Jin, Nieto, and Lu 2020) and the bi-objective coverage location model (Conrow, Murray, and Fischer 2018).

Despite the valuable insights provided by various modelling assumptions, a detailed analysis of BS trips is crucial because BS has more detailed trip characteristics than previously assumed. A notable characteristic of BS demand is their relatively low usage, which ranges from approximately 0.22–8.4 trips per day per docked bicycle (Boor 2019), coupled with an average trip distance that is relatively short, between 1 and 5 km (Du and Cheng 2018; Willberg, Salonen, and Toivonen 2021) and the multi-segment nature of BS trips (Eren and Uz 2020). Meanwhile, existing studies tend to represent BS demand as aggregated points, simplifying population data and the big data of

BS usage. This method of condensing information into aggregated demand data fails to account for the critical characteristic of BS demand, which is multi-segment trips. Ideally, BS demand should be represented at a microscopic level as individual representations, which also capture the behaviour of multi-segment trips. Few studies have attempted to illustrate the multi-segment nature of BS. For example, (Caggiani, Colovic, and Ottomanelli 2020; Yuan et al. 2019) segmented the BS trip into walking to the nearest station, biking, and then walking to the final destination. However, the demand in this model is still presented in an aggregated form, thus not fully representing the small-scale nature of BS demand.

Aggregate data fails to capture the detailed behaviours of travellers and their responsiveness to transportation systems (Kagho, Balac, and Axhausen 2020). Agent-based models (ABM) provide an appropriate method for simulating this complexity. ABM can model a system as a collection of autonomous decision-making entities called agents that interact with each other (Bonabeau 2002). For example, (Soriguera, Casado, and Jiménez 2018) implemented an ABM simulation in Matlab, categorising agents into four entities: stations, bikes, users, and repositioning trucks. The microscopic simulation tool MATSim (Horni, Nagel, and Axhausen 2016) was employed by Diallo, Gloriot, and Manout (2023) to evaluate the effects of BS and e-scooters on current travel modes and similarly by Cai, Ong, and Meng (2023) to investigate a BS behaviour model. In the latter, BS was depicted through agents characterised by demographic details and a behaviour model that accounted for factors like waiting time, cost, walking and cycling duration, and time spent in transit. However, these detailed simulations did not explore the connection between BS trips and the strategic placement of stations. Additionally, existing investigations into the location of BS stations have mainly concentrated on static predictions of usage rates and locations, neglecting the dynamic interplay between users and locations.

To bridge these gaps, we suggest employing an agent-based simulation using MATSim (Horni, Nagel, and Axhausen 2016). This approach optimises BS stations by considering the dynamic interplay of BSS station design elements and evaluating the effects of profit optimisation on station characteristics. Sec. 3 below provides a detailed explanation of MATSim and the reasons for selecting this method.

Methodology

MATSim is an open-source framework for conducting agent-based transport simulation on a large scale. The framework is composed of various modules that can be used either in combination or as stand-alone components, as illustrated in Figure 1:

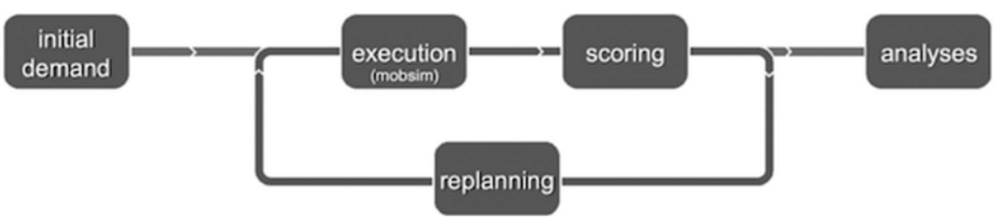

Figure 1. MATSim framework (source: matsim.org).

MATSim provides a demand model framework capable of simulating each traveller individually. Travellers are referred to as 'agents'. Agents interact with each other and also with their surroundings, resulting in effects on the transportation system. These agents are equipped with a daily activity schedule and the ability to make decisions based on the scoring function. Each agent optimises their daily schedule (activity and mode choices) by competing for space–time slots with all other agents on the simulated transportation infrastructure. A schedule's optimality is determined by the best plan scores achieved during this iterative competition. The agent-based simulation MATSim has been utilised to model and simulate various emerging transport modes, including autonomous mobility-on-demand (Ciari, Balac, and Balmer 2015), shared mobility (Balac and Horl 2021), bike-sharing (Cai, Ong, and Meng 2023; Hebenstreit and Fellendorf 2018; 2019; Reck et al. 2021) and electric vehicles (Ewert et al. 2021) alongside the traditional modes.

MATSim often faces criticism for its complexity, extensive data requirement, computational cost and broad scope, which can lead to challenges in interpretation and parameter tuning, as noted by Batty 2008, Bertolini 2017, Maheshwari et al. (2023). Nonetheless, MATSim's capability to simulate transport supply-demand at an individual level is well-suited for representing the conditions of emerging transport modes like shared mobility (Becker et al. 2020), particularly BS, which have different characteristics as explained in Section 2.

Simulation framework

MATSim is capable of simulating different shared mobility modes. The following steps outline the sequence of actions that agents take within the MATSim simulation framework to use the shared bike service provided by the stations:

1. After completing their previous activity at the origin location, agents walk to the closest station and reserve a bike;
2. Agents ride the bike;
3. Agents arrive at the destination station and park the bike;
4. Agents then walk to their final destination.

MATSim can simulate multimodal trips, as shown in Figure 2. Additionally, in this simulation, we assume that bicycles are always available at each station. This is intentional, as our study focuses on the station size as an output of the model.

Figure 2. Multimodal trip using shared bike.

Assignment of trip-discretized Origin–Destination matrices

In this study we used an Origin-Destination (OD) matrix dataset of Vienna Metropolitan Region which was provided by the transport association for Vienna, Lower Austria and Burgenland (Verkehrsverbund Ost-Region). The trip counts from these OD matrices are then transformed into a population plan by incorporating departure and arrival data from the 2013 Austria Household Travel Survey (Bundesministerium für Verkehr; Innovation und Technologie 2013). This population plan file is further enriched with coordinate points for each agent, sourced from Geographic Information System (GIS) traffic cell data in Vienna. We have not yet included sociodemographic characteristics in the population synthesis file because our current inputs based on OD matrix dataset, and we intend to address this limitation in future work.

Behaviour model

In the simulation, agents assess their activities, trips, and mode selections based on a utility (or scoring) function. We use the model developed by (Müller et al. 2022) and simplify it into trip utility functions as depicted in Eq. (1) to Eq. (7). The model from (Müller et al. 2022) includes only four different modes: walking, bicycle, car and public transport. We then modify it by adding an additional mode, which is BS. To detail the context of public transport in Vienna, we categorise public transport into four types: buses, trams, subways and railways. The subway and railway respectively represent the U-bahn, serving local routes within Vienna, and the S-bahn, covering both local and intercity routes, including international connections. The utility for walking, including walking episodes of BS multi-segment trips, is set to 0 as a reference parameter.

$$U_{bikeSharing} = \beta_{ASC_{bikeSharing}} + directUtilityOfTravelTime_{bikeSharing} \tag{1}$$

$$\begin{aligned} U_{car} = {} & \beta_{ASC_{car}} + directUtilityOfTravelTime_{car} + monetaryDis\tan ceRate_{car} \\ & + dailyMonetaryCons\tan t_{car} \end{aligned} \tag{2}$$

$$U_{bike} = \beta_{ASC_{bike}} + directUtilityOfTravelTime_{bike} + dailyMonetaryCons\tan t_{bike} \tag{3}$$

$$\begin{aligned} U_{pt_{bus}} = {} & \beta_{ASC_{pt_{bus}}} + directUtilityOfTravelTime_{pt_{bus}} \\ & + dailyMonetaryCons\tan t_{pt_{bus}} \end{aligned} \tag{4}$$

$$\begin{aligned} U_{pt_{tram}} = {} & \beta_{ASC_{pt_{tram}}} + directUtilityOfTravelTime_{pt_{tram}} \\ & + dailyMonetaryCons\tan t_{pt_{tram}} \end{aligned} \tag{5}$$

$$\begin{aligned} U_{pt_{subway}} = {} & \beta_{ASC_{pt_{subway}}} + directUtilityOfTravelTime_{pt_{subway}} \\ & + dailyMonetaryCons\tan t_{pt_{subway}} \end{aligned} \tag{6}$$

$$\begin{aligned} U_{pt_{rail}} = {} & \beta_{ASC_{pt_{rail}}} + directUtilityOfTravelTime_{pt_{rail}} \\ & + dailyMonetaryCons\tan t_{pt_{rail}} \end{aligned} \tag{7}$$

In our study, we calculated the *directUtilityOfTravelTime* for each mode based on the model by (Müller et al. 2022). The behaviour model from (Müller et al. 2022) was developed based on the study of a joint time-assignment and expenditure-allocation model from (Hössinger et al. 2020) and a simplified Value of Travel Time Saving (VTTS) model using a revealed and stated preference mixed logit model from (Schmid et al. 2019) in Austria. These studies use a time-use framework from (Jara-Diaz 2000; Jara-Díaz and Guevara 2003) to model individual travel demand. The time-use model framework proclaims that travel can be seen not only as a commodity resulting in disutility but also as an activity that has the value of travel time as a resource. The latterhas been used by (Müller et al. 2022) to describe the utility (scoring) function in their behaviour model, meaning that travel receives not only the typically negative direct marginal utility of $\beta_{travel,\, mode}$ but also a penalty from the marginal utility of time as resources (Nagel et al. 2016). In (Müller et al. 2022), the value of travel time as direct marginal utility has been estimated jointly with travel time as a resource and represented by the VTTS. In the meantime, travel time as a resource is also calculated by (Müller et al. 2022) and represented as the Value of Leisure (VoL). Both values, along with the constants, were estimated for four types of mode and ten different population groups.

The study from (Hössinger et al. 2020) mentioned that they use microeconomics theory and the valuation of travel time from (DeSerpa 1973) to examine the VTTS further and conclude that VTTS equals the VoL minus the Value of Time Assigned to Travel (VTAT), where VTAT represents the direct (dis)utility derived from the time spent in the travel activity. Since we use a different dataset of agents, without specific population groups and activities, this study simplifies the behaviour model from (Müller et al. 2022) by only taking the value of travel time as direct (dis)utility or VTAT. We separate VTAT from VTTS by taking the difference between VoL and VTTS for each population group in (Müller et al. 2022), taking the average value and assigning it as the value of *directUtilityOfTravelTime* for our trip utility functions for modes walk, bike, car and public transport as illustrated in Eq. (1) to Eq. (7). Due to data limitations, the same figures of *directUtilityOfTravelTime* from public transport were applied across all four utility functions for bus, tram, subway and railway.

For BS, the parameter of $directUtilityOfTravelTime_{bikeSharing}$ was determined by taking the $directUtilityOfTravelTime_{bike}$ and adding the bike-sharing rental cost of 1.2€/hour. The *dailyMonetaryConstants* were assumed to be 13.521€/day for cars, 1€/day for bikes, and 1€/day for public transport modes (bus, tram, subway, rail). The *monetary distance rate for a* car was set at 0.09€/km. These parameters, *dailyMonetaryConstant* and *monetaryDistanceRate*, represent financial expenditures and are calculated as direct disutilities in the utility functions. We manually tuned the alternative specific constants to match with mode share data from ITS Vienna's Visum OD matrices, as shown in Figure 3.

Station optimisation

The investment in establishing a BS station can be categorised into installation costs, operational costs, and maintenance costs. We obtained detailed cost parameters from

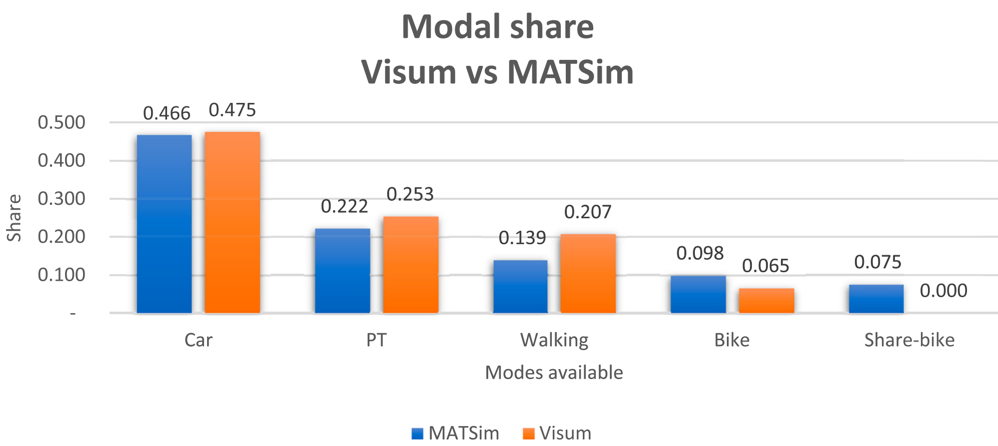

Figure 3. Modal share comparison between Visum and MATSim.

a Vienna shared modes operator, MO. Point (mopoint.at), as detailed in Table 1, including:

1. The one-time/fixed installation cost, assuming no land rental cost, includes the purchase of docking stations for the bike, the bike itself, the key for the bike, a signboard, and floormarking.
2. Operational and maintenance costs encompass depreciation, energy expenses, licensing fees, reinvestment costs, rebalancing costs, and cleaning costs.

We developed a protocol to test various station configurations in the simulation, calculating profit based on generated demand, as shown in Figure 4. For our purposes, 'configuration' pertains to the quantity and location coordinates of stations. The station optimisation protocol, aimed at maximising profit, consists of the following steps:

1. Initial State: The initial configuration of station locations with all stations being open, indexed by i and denoted as P^i, is prepared as the starting point for the simulation;

Table 1. Cost parameters of bike-sharing station installation in 2022.

One-time installation costs		Operational & maintenance costs	
Bike per each		Depreciation (per bike/month)	10 €
City bike	1000 €	Depreciation (per e-bike/month)	40 €
City bike key	150 €	Maintenance (per bike/month)	100 €
e-bike	4500 €	Maintenance (per charging station/month)	17 €
e-bike key	150 €	Cleaning (per station/month)	45 €
Station		Reinvestment (per bike/month)	10 €
Bicycle dock per each	400 €	Reinvestment (per station/month)	10 €
Signboard	16650 €	Rebalancing (per bike/month)	12 €
Floor marking	4900 €	Licences (per month)	15 €
Charging station (5 points)	9000 €	Energie (per signboard/month)	1 €
		Energie (per e-bike/month)	15 €

Note: this study does not use variable e-bike and station with charging.

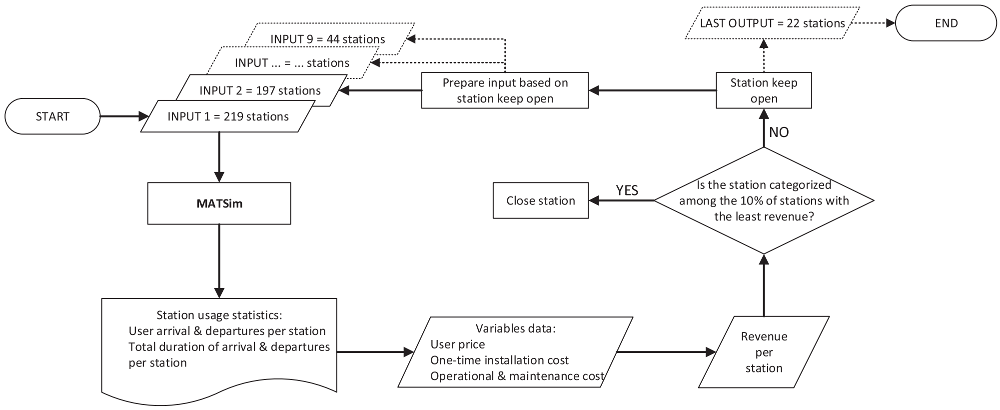

Figure 4. Station optimisation protocol.

2. The total nett profit per P^i is calculated using the given formula:

$$\sum NP_j^i = gross\ income_j^i - \ cost\ of\ station_j^i \tag{8}$$

3. Simulation Execution: The simulation is run to capture the dynamics interaction between user behaviour and demand per station;
4. Usage Statistics: the simulation outputs generate usage statistics for each station, including the number of users per station and the total duration of trips per station. The usage statistics per station are evaluated by considering various cost variables using the following formula.

   P^i = a configuration of stations, indexed by i; $user_j^i$ = number of users of station j for each $j \in P^i$; td_j^i = total duration of trips per stations j for each $j \in P^i$ (minute); up_j^i = user price per bike used by $user_j$ for each $j \in P^i$ (€/minute); oc_j^i = operational cost per bike used by $user_j$ for each $j \in P^i$ (€/minute); smc_j^i = stations maintenance cost per station location opened for each $j \in P^i$ (€/minute); sfc_j^i = stations fixed cost per station location opened for each $j \in P^i$(€/minute);

   Station j in system i obtains nett profit:

   NP_j^i = nett profit per station location opened for each $j \in P^i$ (€/day);

$$NP_j^i = gross\ income_j^i - \ cost\ of\ station_j^i \tag{9}$$

$$NP_j^i = \ (td_j^i\ .\ up_j^i) - (td_j^i\ .\ (oc_j^i + smc_j^i + sfc_j^i)) \tag{10}$$

5. NP_j^i is then in descending order, from the most profitable to the least profitable stations;
6. Based on step 5, the 10% of stations with the lowest net profit are identified and removed, resulting a new configuration to be input to the next cycle.

steps 2–6 are repeated incrementally until only 10% of the original stations remain in the cycle. The 10% station reduction is an arbitrary choice that suffices to illustrate the approach without requiring excessive computations.

Case study

The study's experimental model area covers the broader region of Vienna, Austria. Vienna's local government has strategically placed 219 BS stations across the city next to public transport transfer points, as illustrated in Figure 5. The station location coordinates were sourced from Wiener Linien, the local government operator, and verified using the OpenStreetMap database and bikesharemap.com through overpass-turbo.eu. With 219 identified stations, the city of Vienna is categorised into three regions for analysis: Inner (Districts 1–9 with 82 stations), Outer (Districts 10–20 and 23 with 99 stations), and Upper (Districts 21 and 22 with 38 stations).

Simulation results and analysis

In this section, the simulation results are presented, quantitatively in Section 4.1 and qualitatively in Section 4.2.

Quantitative results

Figure 6 and Figure 7 allow us to observe the relative number of average users per station, total users and total profit across different configurations (values on the x-axis represent number of open stations). In Figure 6, there is an upward trend in the average number of users per station, while the total number of users slowly decreases. Adding more stations to the cycle increases their accessibility to potential users.

Figure 7 illustrates the varying profit conditions per cycle resulting from changes in the number of stations and total users. The gradual closure of stations impacts the total profit from cycle to cycle. Initially, profit increases due to reduced one-time

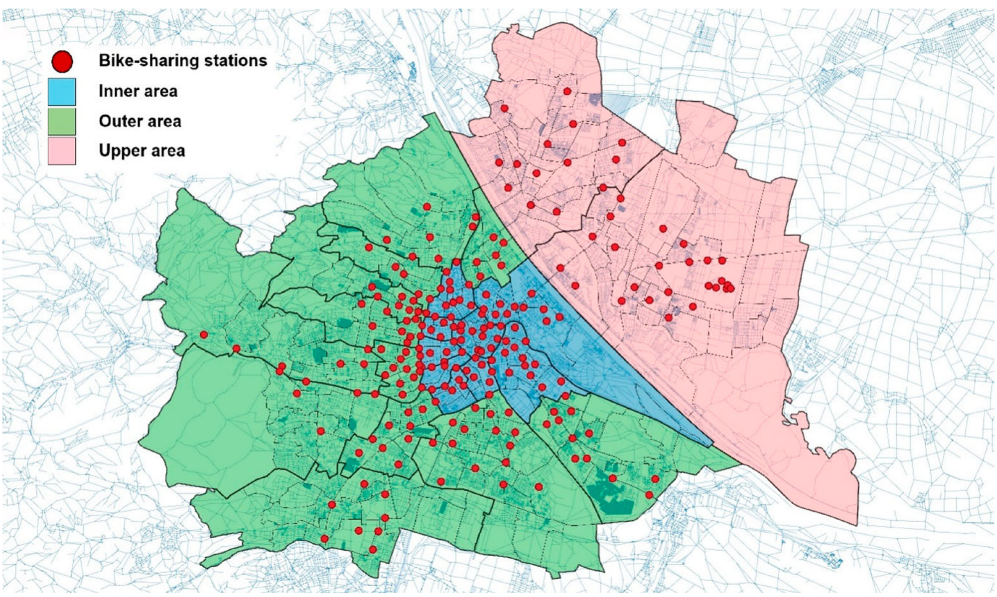

Figure 5. Locations of BS stations in Vienna.

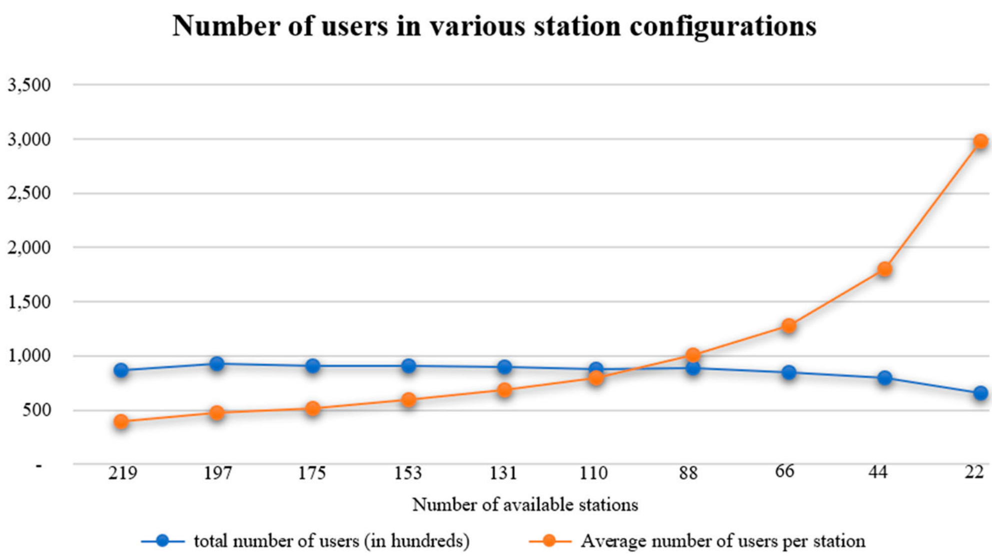

Figure 6. Number of users in various station configurations.

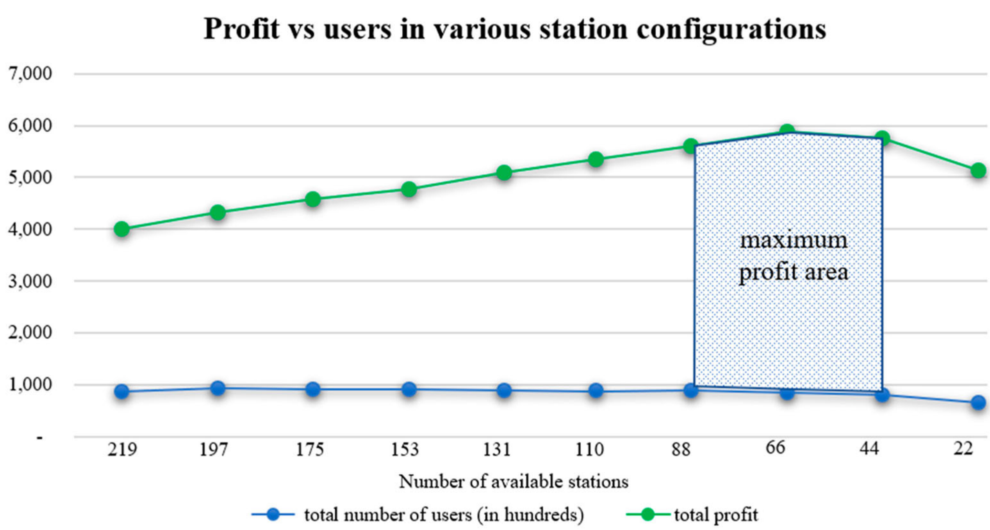

Figure 7. Total profit and total users in various station configurations.

station investment costs, reaching a peak when the number of remaining stations is 66. It then gradually declines due to diminishing user numbers.

The comparison of profit and users across different station configurations, allows us to identify the most profitable station configuration, which is the configuration with 66 stations. The maximum profit area shown in Figure 7, featuring a range of 44–66 stations, can serve a nearly identical total number of users and generate a similar total profit. A detailed investigation into the most profitable station configuration should focus on this range of 44–66 stations, as illustrated by the maximum profit area.

Table 2. Descriptive features of station.

	**Generator station (GS)** This marker represents the station with more user departures than arrivals. This indicates the station's potential to generate BS trip for its corresponding catchment area.
	**Attractor station (AS)** This marker represents the station with more user arrivals than departures. This indicates the station's potential to attract BS trip for its corresponding catchment area.
	**Interchange station (IS)** This marker indicates a station with a relatively balanced number of user departures and arrivals. This suggests that the station has the potential to serve as a transfer point for BS trips in its corresponding catchment area.

Spatial results

This section examines the changes in spatial and environmental parameters resulting from variations in demand per station. Spatial parameters are represented by: (1) total population, (2) population density, and (3) gender dominance per sub-district, derived from Vienna's 2021 statistical data from 23 districts and 250 sub-districts. Built environment parameters are identified based on GIS data from various Points of Interest (PoI), including public transport stops, car-sharing spots, electric charging points, bike and scooter parking, educational institutions, cultural venues, dining options, parks, healthcare facilities, public services, retail locations, and sports facilities. Stations are analysed within a 200-metre radius to assess accessibility, with PoIs within this area counted to categorise stations into three types based on PoI density: Low PoI coverage (1–75 PoIs), Medium PoI coverage (76–150 PoIs), and High PoI coverage (>150 PoIs). Through this process, parameter (4) station type based on coverage of Points of Interest (PoI) is determined.

The demand per station generated by the simulation identifies the frequency of users departing from and arriving at each station. This frequency is visualised with descriptive features in Table 2, where a larger mark indicates higher frequencies. This process yields parameter (5) type of station based on the number of user departures and arrivals as an additional spatial information from the simulation with profit optimisation.

These five parameters are subsequently utilised to quantify changes in spatial and built environment resulting from variations in demand per station. The quantification of these changes is examined per observation area – inner, outer, and upper – for configurations of 219, 131, and 66 stations as detailed in Table 3 below.

Meanwhile, changes in demand per station are visualised for configurations of 219 and 66 stations in each observation area as follows.

Inner area

The Inner Districts of Vienna, covering districts 1–9 with a 2021 population of 430,996 across 53 sub-districts, are the city's core. Figure 8 shows 82 BS stations deployed within 400–1000 meters of each other, highlighting the coverage of Points of Interest (PoIs) and nearby population density.

Table 3. Quantification of changes in spatial and built environment due to variations in station demand.

Spatial and sociodemographic indicator		Number of stations across three station configurations								
		219 sta			131 sta			66 sta		
Observation area		Inner	Outer	Upper	Inner	Outer	Upper	Inner	Outer	Upper
(1) Total population										
Low	0–10,000 inhabitants	55	43	20	29	26	17	15	12	9
Medium	10,001–20,000 inhabitants	27	51	18	17	29	8	8	12	6
High	>20,000 inhabitants	0	5	0	0	5	0	0	4	0
(2) Population density										
Low	0–2 persons per m^2	48	56	35	26	32	22	14	12	13
Medium	3–4 persons per m^2	32	36	3	18	22	3	8	12	2
High	>4 persons per m^2	2	7	0	2	6	0	1	4	0
(3) Population based on gender composition										
Female dominant		72	68	35	41	41	23	21	19	15
Male dominant		10	31	2	5	19	2	2	9	0
(4) Station type based on PoI's coverage (within 200 m buffer)										
Low	1–75 PoI's coverage	60	90	37	34	56	24	15	26	14
Medium	76–150 PoI's coverage	17	8	1	9	3	1	6	1	1
High	> 150 PoI's coverage	5	1	0	3	1	0	2	1	0
Additional spatial information from simulation with profit optimization										
(5) Type of station based on the number of user departures and user arrival										
Generator station		34	43	17	26	23	12	11	19	5
Attractor station		16	19	4	12	15	6	10	8	6
Interchange station		32	37	17	8	22	7	2	1	4

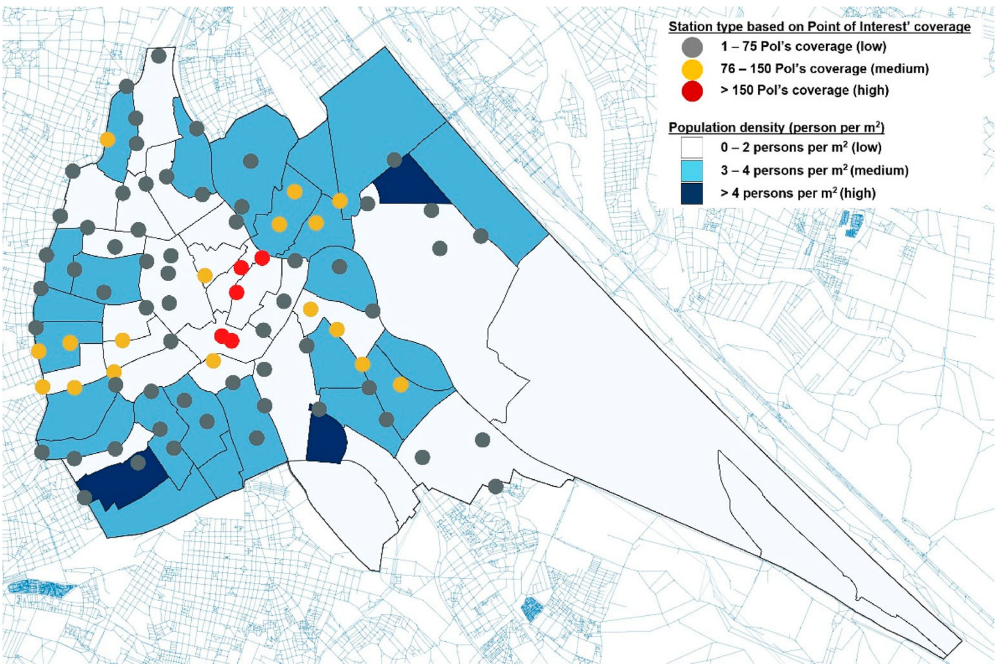

Figure 8. Locations of 82 BS stations in the inner area of Vienna.

With a full configuration of 219 stations, they are mainly placed in areas with medium to low population density due to the scarcity of high-density sub-districts. The station type is generally having low coverage, with only five stations having

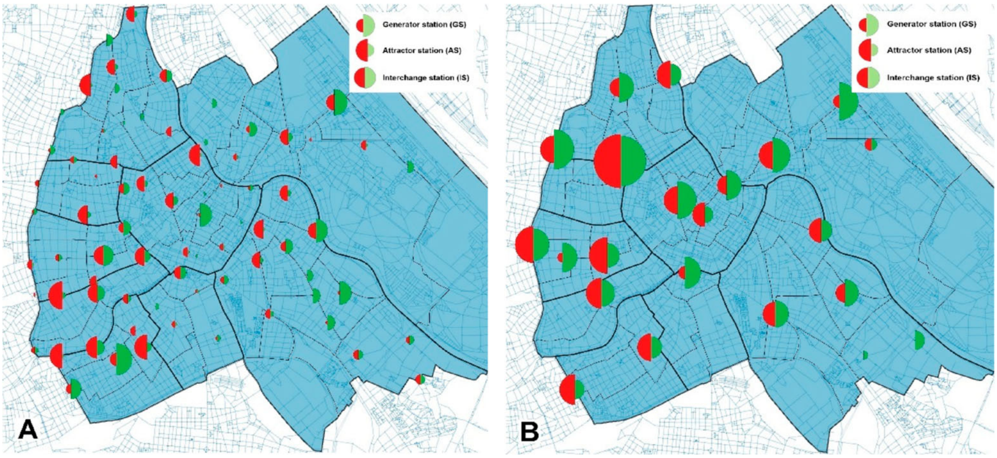

Figure 9. Identification station types in the inner area (A) with 219 stations and (B) with 66 stations.

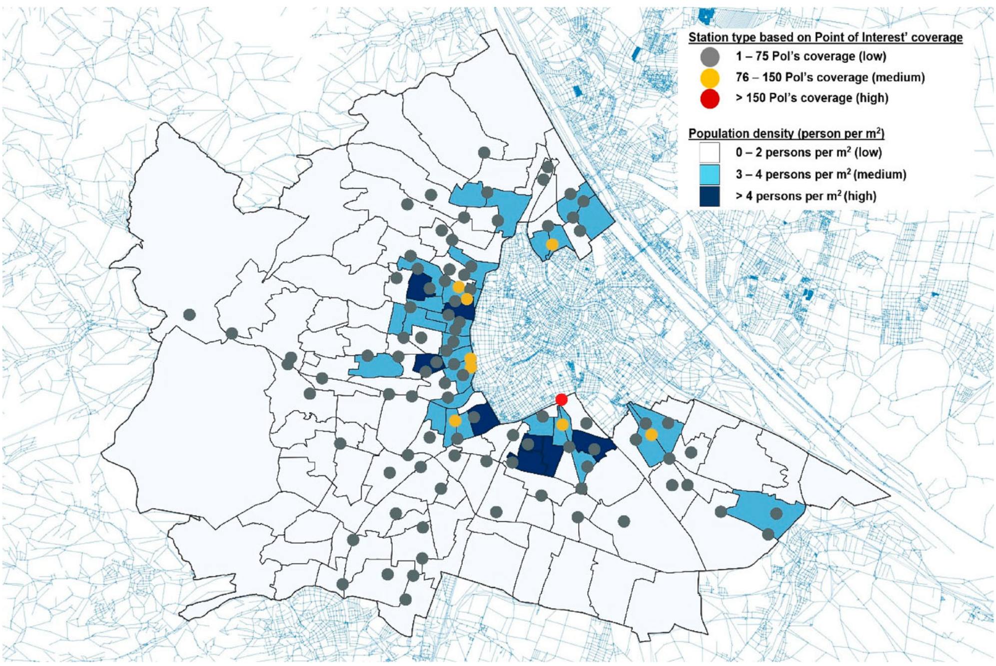

Figure 10. Locations of 99 BS stations in the outer area of Vienna.

high coverage. Generator and interchange stations are more common than attractor types in this area, as illustrated in Figure 9 part A. The optimised configuration from the simulation, depicted in Figure 9 part B with 66 stations, shows significant adjustments. These include a major reduction of stations in low-density, low-PoI areas, a shift towards more generator and attractor stations, and a notable size difference for an interchange station.

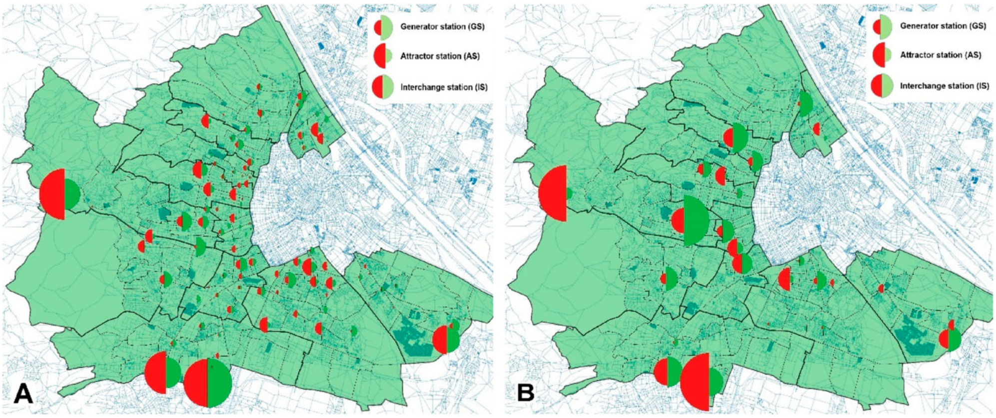

Figure 11. Identification station types in the outer area (A) with 219 stations and (B) with 66 stations.

Outer area

The Outer Districts of Vienna, encompassing districts 10–20 and 23, had a population of 1,117,231 in 2021 across 135 sub-districts. Figure 10 shows 99 BS stations, primarily around the periphery of the inner districts. In the 219-station configuration, stations are predominantly distributed in lower-density sub-districts, with a secondary focus on medium-density areas, mainly featuring stations with low PoI's coverage.

Generator and interchange stations are more common than attractor types in these outer districts as illustrated in Figure 11 part A. Following optimisation simulations, as depicted in Figure 11 part B, necessary adjustments include significant reductions

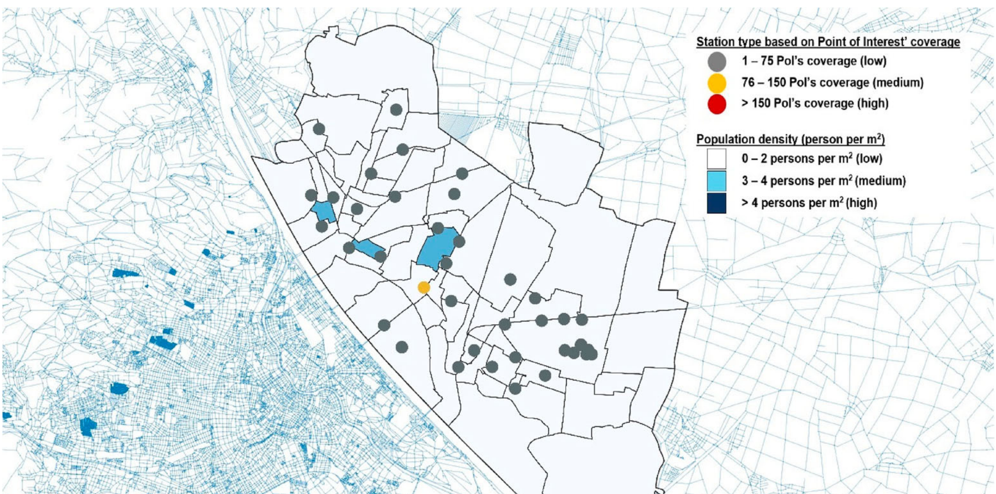

Figure 12. Locations of 38 BS stations in the upper area of Vienna.

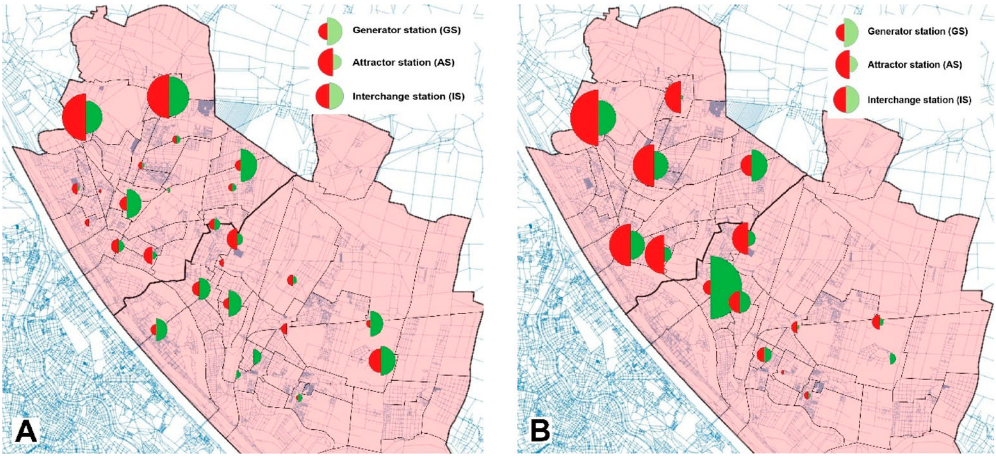

Figure 13. Identification station types in the upper area (A) with 219 stations and (B) with 66 stations.

in stations: up to 20% in lower-density areas and 33% in medium-density areas. Closures affected 3 out of 7 stations in high-density areas. The station mix has shifted towards more generator and attractor stations, with one interchange station remaining. Notably, there are two large attractor stations and one large generator station, with the sizes of other stations ranging from moderate to small.

Upper area

Vienna's upper area, comprising two large districts with a 2021 population of 1,117,231 across 62 sub-districts, blends historical and modern elements. Despite its size, only 38 BS stations are deployed due to low population density, as shown in Figure 12. In the 219-station configuration, stations are mainly located in low-density, low-POI areas, with most classified as generator and interchange stations as illustrated in Figure 13 part A. Post-simulation optimisations, depicted in Figure 13 part B, reveal important adjustments. Stations in medium-density areas remain largely unchanged, those too closely positioned are removed, and there's a shift towards a balanced mix of generator, attractor, and interchange station types. This results in a reduction of stations in low-density areas by nearly two-thirds.

Discussion

The simulation findings in Vienna suggest an overabundance of stations, with 219 distributed across the city. Positioning only 66 stations, predominantly of the generator type, followed by attractor and then interchange types, as shown in Figure 14, suggests a profit-prioritizing solution and underscores the need for optimising station numbers. However, considering Vienna's ambition to transform BS stations into comprehensive mobility hubs, optimising to only 66 stations – though profit-efficient – may overlook the transformation's broader benefits. Distributing 219 bike-sharing stations and integrating them with the existing public transportation network as depicted in Figure 15 goes beyond just profitability. It can serve as an initial step to improve urban mobility, accessibility, and sustainability.

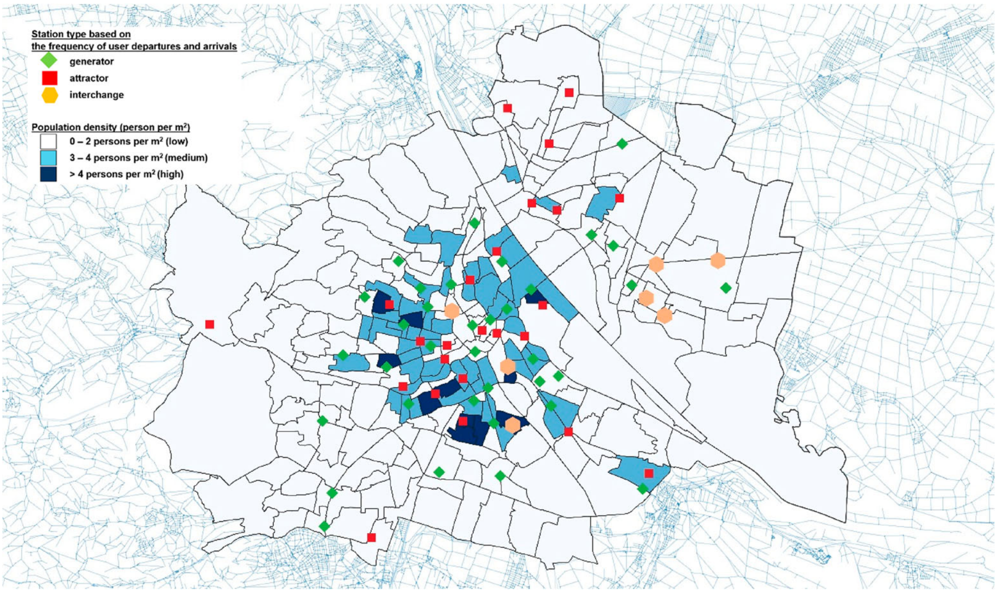

Figure 14. Optimal configuration of BS station with the station type.

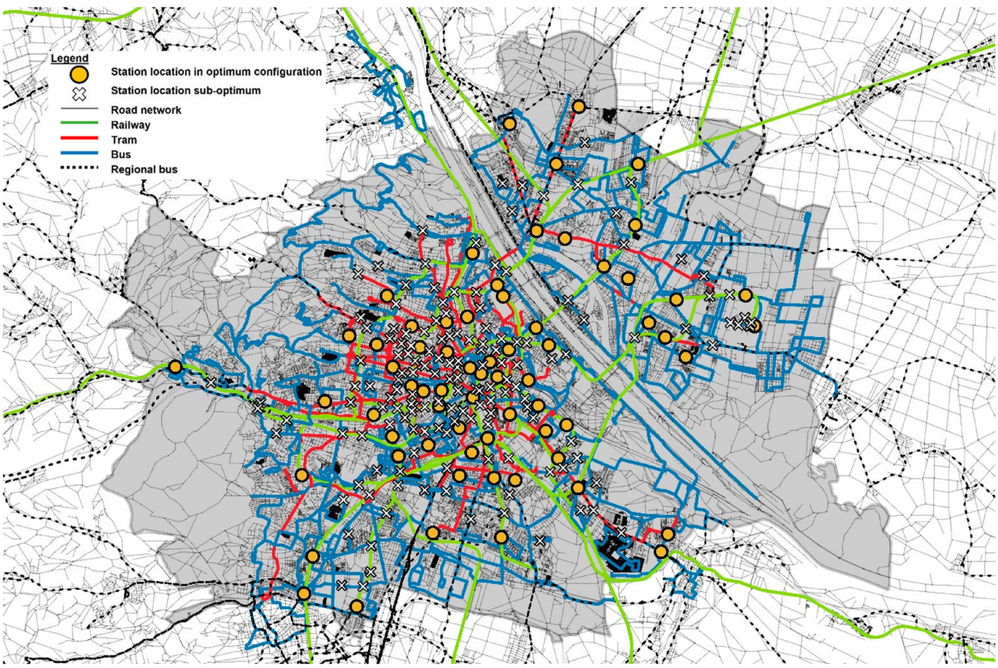

Figure 15. Optimal configuration of BS station with the transport network.

Simulations in our study can detail the number of user arrivals and departures per station by considering different station location configurations based on profit optimisation functions. The behaviour model in the simulation allows for predicting demand according to BS user characteristics, where the success of BS is influenced by system usage (Horjus et al. 2022). Knowing the demand predictions per station aids operators in planning the number of bicycles to distribute and the bike re-balancing process (Schütze 2023; Soriguera, Casado, and Jiménez 2018). By incorporating and quantifying spatial and built environment elements, and modifying the configuration of the location, planners and policymakers can review the structure of Vienna, examine the distribution of station locations in accordance with principles such as social justice, inclusion and democratic values (Graf and Hansel 2023), predict how residents near the station react to the transition to sustainable mobility (Graf, Hansel, and Wagner 2023). The change in the location configuration of the BS station in the simulation also contributes to the development of ideas for a network of shared mobility hubs, consistent with local policy objectives and regulatory contexts, while contributing to sustainable urban mobility (Coenegrachts et al. 2021).

Summary and outlook

Through MATSim simulation with optimisation processes, despite its current limitations, we can observe changes in the following elements:

1. The number and location of stations in different configurations resulting from profit optimisation. This element aids in the decision-making process for location planning by providing an optimal configuration of stations maximising demand and revenue.
2. User arrivals and departures per station reflect real-world station sizes and scales, enabling vehicle distribution predictions. This aids in forecasting vehicle distribution over time, helping operators plan operational aspects.
3. Station types are based on the number of user arrivals and departures per station. By integrating insights into spatial and built environments, this analysis helps understand usage patterns influenced by station locations and nearby facilities. This allows urban planners to tailor station layouts to each area's unique attributes, advancing the development of comprehensive mobility hubs.

The future improvements will focus on refining choice behaviour models and enhancing the integration of the bike-sharing behaviour model with existing models. Additionally, the protocol for optimising station locations will undergo further refinement. It is important to recognise the study's constraints. The heuristic-based location optimisation protocol serves as a guide rather than an optimal solution, lacking a guarantee of finding the optimal arrangement. This limitation stems from the protocol's inability to reconsider previously excluded stations in new optimisation rounds, which could compromise the effectiveness of the results.

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