Delft University of Technology

CIE5050-09 Additional Graduation Work

Land Use Impacts of Shared Micromobility Services

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Abstract

Nowadays, limited bike parking spaces have been a severe problem to be solved in the Netherlands. Shared bikes are considered ideal solutions, as well as other emerging shared micromobility modes, e.g., shared e-bikes, e-scooters and e-mopeds, since they can help utilise vehicles better and alleviate more occupying land space. Moreover, shared micromobility modes have a great potential to attract private car users and achieve a modal switch from private cars to them. In this case, this research aims to understand how the sum of parking areas changed by the modal switch from private cars and bikes to shared micromobility modes. A calculation approach of parking areas will be proposed and applied in an agent-based simulation model mimicking the mode choice of travellers in Delft. Moreover, shared micromobility modes regarding vehicle characteristics (speed and cost) will be differentiated, so their impacts on mode choice and land space will also be investigated. Additionally, this study made a sensitivity analysis of coefficients of utility functions to test the reliability and validity of the results.

1 Introduction

The emergence of shared micromobility services has gained popularity across countries. Many cities have at least one shared micromobility mode in operation. Wikipedia defines micromobility as "a range of small, lightweight vehicles operating at speeds typically below 25 km/h (15 mph) and driven by users personally" (Wikipedia, n.d.). Shared micromobility thereby refers to light and low-speed vehicles for shared use. Nowadays, shared bikes, shared e-bikes, shared e-scooters, and shared e-mopeds are often discussed and considered the most popular shared micromobilty modes. E-micromobility vehicles can provide longer-distance and faster-speed trips with less physical energy, giving travelers more mode choices. There are two well-known roles for shared micromobility services. The first is a feeder mode to integrate with public transport by completing the first/last mile, achieving multimodal trips. The second is a substitution mode, replacing other modes for single-modal trips (Liao & Correia, 2022; Yanocha & Allan, 2019). Shared micromobility is undoubtedly for short-distance trips, no matter which kind of role it takes.

Currently, the Netherlands has limited bike parking spaces, especially in train stations (van Goeverden & Correia, 2018). Numerous bikes are idle, occupying excessive parking spaces. Shared micromobility service is an appropriate solution to utilize spaces and vehicles better. Two typical roles of shared micromobiltiy will lead to a modal shift from private micromobiltiy vehicles to shared ones. It can reduce the number of idle micromobility vehicles and the demand for parking spaces. Satisfy as much demand as possible while not wasting any vehicle by over-supply leading to idle vehicles; in other words, it is the match between supply and demand. Also, a modal shift from other modes to shared micromobility modes cannot be ignored. Total parking spaces could vary significantly due to the modal shift from different modes and the proportion of the modal shift.

From a literature review on land use impacts of shared micromobility, rare studies focus on urban parking spaces to the author's best knowledge. The most related work is Zhang et al. (2015), which investigates the impacts of shared automated vehicles (SAV) on parking spaces. A literature review will be conducted first, and the influential primary factors will be summarised later. The third section will design a framework including factors. The fourth section will propose a calculation approach regarding the number of parking spaces for shared and private vehicles and implement the framework in a developed Python programming environment simulation model. A sensitive analysis of values of critical parameters will be followed. The conclusion and reflection statement will be at the end of the report. As mentioned above, the research goal is to understand if various kinds of shared micromobility modes can actually reduce parking demand and relieve land space. The research question is derived as below:

What are impacts of various shared micromobility modes on parking spaces?

2 Literature review

The most common shared micromobilty modes are shared bikes, e-bikes, e-scooters, and e-mopeds. Though they are defined as the same kind of mobility service, differences still exist, whether in demand or supply. Understanding the differences between these modes is necessary to determine which modes will be included in this research. Related literature has been reviewed in three parts: user attributes, usage patterns, and vehicle characteristics. The former two represent the demand side of mobility service while the latter represents the supply side. Several studies did comprehensive reviews through case studies in different cities (Shaheen & Cohen, 2019; Liao & Correia, 2022; Yanocha & Allan, 2019; Reck et al., 2021). Note that the following are findings from distinct literature, which can work in most cases. User attributes are relatively similar regarding gender, age, income level, and living area (Shaheen & Cohen, 2019; Liao & Correia, 2022). With regards to vehicle characteristics, the average speed of shared e-scooters and (e)-bikes (25km/h) is relatively lower than shared e-mopeds (45km/h) (Yanocha & Allan, 2019). Shared micromobiltiy modes are mostly taken for short-distance trips; thus, the value of speed can be crucial when travelers choose a mode. The battery range of e-scooters (22-35km)is far lower than all other modes (80-90km), which has little influence on one trip but affects the availability of e-vehicles considering times of charging. Each e-scooter or e-moped can be occupied by 1-2 persons, while (e)-bikes can only support one person. Concerning usage patterns, the trip distance of shared e-scooters is lower than the other three modes. Besides, shared bikes are more negatively affected by increasing trip distance than share e-bikes, so the trip distance of bikes is larger than e-bikes (Reck et al., 2021). Shared (e)-bikes are primarily used for commuting trips and being integrated with public transport, while shared e-scooters are mainly for leisure during the off-peak hour. Moreover, Reck et al. (2021) distinguishes docked system and dockless system and finds that docked shared (e)-bikes are particularly preferred for commuting during peak hours than dockless shared (e)-bikes. Four modes are differentiable regarding at least one aspect, even though some aspects will not be modeled in this research. Considering shared e-scooters are not allowed in the Netherlands, they will be out of scope in this research.

Numerous papers explore the impacts on land use of shared micromobility, mostly on cycling and car driving lanes. According to Yanocha & Allan (2019), the road width may be required to be widened for building infrastructures separating shared micromobility considering safety. Increased demand for shared micromobility will eventually lead to a new allocation of road space which assigns wider lanes for (e)-bikes, e-scooters, e-mopeds (Liao & Correia, 2022). One car's size equals spaces occupied by ten bikes, so bikes can save much more space whether for parking or riding/driving, especially for single-occupancy trips (Yanocha & Allan, 2019).

For any shared mode, docked/station-based and dockless/free-floating systems are distinct concerning multiple aspects. Travelers can access shared mobility services more quickly when using a dockless system than a docked system. On the one hand, it could increase the attractiveness of shared mobility. On the other hand, it can raise the potential that vehicles will be randomly parked, affecting travelers of other modes and lowering the efficiency of utilization of urban spaces. Liao & Correia (2022) concluded that usage patterns, determinants of demand, user group, and impacts of shared micromobility might differ depending on whether the system is docked or dockless. For instance, docked system is more often used for commuting, and the integration of shared micromobility modes with public transport can increase the number of multimodal trips more significantly than the dockless system (Reck et al., 2021). Moreover, they recommend that city regulators and companies could leverage and extend this concept by introducing "mobility hubs," which refers to hubs that include multiple transport modes and offer transfer in a more convenient way. The role of shared micromobility in completing multi-modal trips can stimulate higher demand for shared micromobility if the integration between public transport reduces. This research will determine a station-based shared micromobility system that incorporates mobility hubs to reflect the shared micromobilty as much as possible.

Zhang et al. (2015), Mclean et al. (2021) and Xanthopoulos (2022) focus on simulation models for shared mobility service. Zhang et al. (2015) develops a simulations model for studying the impacts on parking demand of free-floating shared autonomous vehicles. They designed several scenarios on different values of fleet size and found that parking demand can decrease with the system's reduction of the fleet size. However, an unreasonable small fleet size will deteriorate service quality. Mclean et al. (2021) also developed a simulation model to evaluate the impacts of different e-scooter management policies (e.g., fleet size, battery re-charging strategies, and urban parking infrastructure locations) on the efficacy of the free-floating e-scooter system. Experiment results demonstrate the importance of proper site selection for parking areas and battery charging infrastructure. Also, they suggest that increasing the number of parking zones is far more effective than increasing the number of parking spaces in existing zones. This finding is similar to another work (Xanthopoulos, 2022) which focuses on the strategic planning of mobility hubs for optimizing social welfare. The results show that having more hubs with a smaller fleet size is more beneficial than having fewer with a larger fleet size.

Based on the work of Reck et al. (2021), research on shared micromobility can be categorized into two topics: demand-side and supply-side. Demand-side research mainly concentrates on factors that influence demand. It can be divided into internal ones (e.g., user socio-demographics), external ones (e.g., built environment, geography, weather), and trip-related ones (e.g., trip distance, destination). The first paragraph discusses internal and trip-related factors in detail, referring to user attributes and usage patterns. Regarding external factors, Cheng et al. (2022) studied the built environment effects of integrated use of urban transit rail and shared bikes and listed several variables of the built environment such as population density, employment density, land use mix, etc., Xanthopoulos (2022) concluded that areas with higher population density are prioritized when lower budgets are invested in building the mobility hubs. Similarly, supply-side research can be classified into internal and external factors. Internal factors refer to what services the system and vehicles can offer. For system, Fistola et al. (2022) mentioned three criteria to be met: accessibility, distribution, and reachability, respectively: What is the density of stations (distribution)? Whether people can find stations easily (reachability)? Whether stations have available and functional vehicles for use (accessibility)? In other words, system factors refer to the number of locations of stations, parking spaces of each station, and vehicle fleet for each mode. As aforementioned in the first paragraph, vehicle factors refer to vehicle characteristics for each mode, such as battery range and average speed. Regarding influential external factors on supply, how much land can be used for shared micromobility is an essential precondition; also, the budget can play an important role. Considering multimodal trips, the existence of public transport modes is also vital.

The book of van Wee et al. (2013) summarised four most-often mentioned land use variables: density, neighborhood design, mixed land use, and distance to public transport connections. Also, they discussed how these variables affect travel behavior, as well as their internal interactions. Higher-density area offers the possibility of traveling less as people can reach the exact locations for their activities while traveling fewer kilometers, saving time and money. A similar conclusion of mixed land use is drawn: an area with several categories of land use distributed evenly could lead to less travel due to an average shorter distance for their activities if mode choice is constant. If not, slower modes such as walking and biking will be chosen more. Neighborhood design refers to road infrastructure design, allocation of space for several land-use categories, the architecture of the built environment, and the presence of features such as parks and trees. Slower modes could be more attractive if offering better pavements and cycling lanes. Concerning distance to public transport connections, if dwellings and offices are closer to public transport, less access and egress time are required for public transport, then a higher share of public transport.

As pointed out by Reck et al. (2021), research on shared mobility is divided into supply and demand, which can be further divided into external and internal factors influencing supply and demand separately. The main influential factors that affect parking spaces are demonstrated in table 1.

To conclude, there are four identified research gaps. Firstly, papers on shared micromobility are usually involved with the free-floating system, while the station-based system is rarely investigated. Secondly, a limited number of studies develop simulation models for shared micromobility modes. Simulating tools functional for shared micromobility are few, while shared (e)-cars are applied more often (Tzouras et al., 2022). Thirdly, most studies on shared micromobility only concentrate on one mode, whether on demand-side, supply-side, or integrated use for multimodal trips. Fourthly, no study explores the impacts on parking spaces of shared micromobility modes. This research will focus on vehicle supply, studying impacts on parking spaces of shared micromobility and their differences in a station-based system. The following section will discuss the proposed model framework further in detail.

Table 1: Main influential factors

Categorization	External	Internal		Trip-reltated
Demand	Built environment, geography, weather (Reck et al., 2021)	User socio-demographics (Reck et al., 2021)		Destination, time of day, distance (Reck et al., 2021)
Supply	Built environment (density, mixed use, neighborhood design, distance to PT connections) (van Wee et al., 2013), budget (Xanthopoulos, 2022)	System: Location and number of stations, size (parking spaces) of each station, vehicle fleet for each mode, relocation rule (Zhang et al., 2015; Xanthopoulos, 2022; Mclean et al., 2021)	Vehicle: Characteristics on speed, battery range and occupancy (Yanocha & Allan, 2019; Liao & Correia, 2022)	

3 Model framework

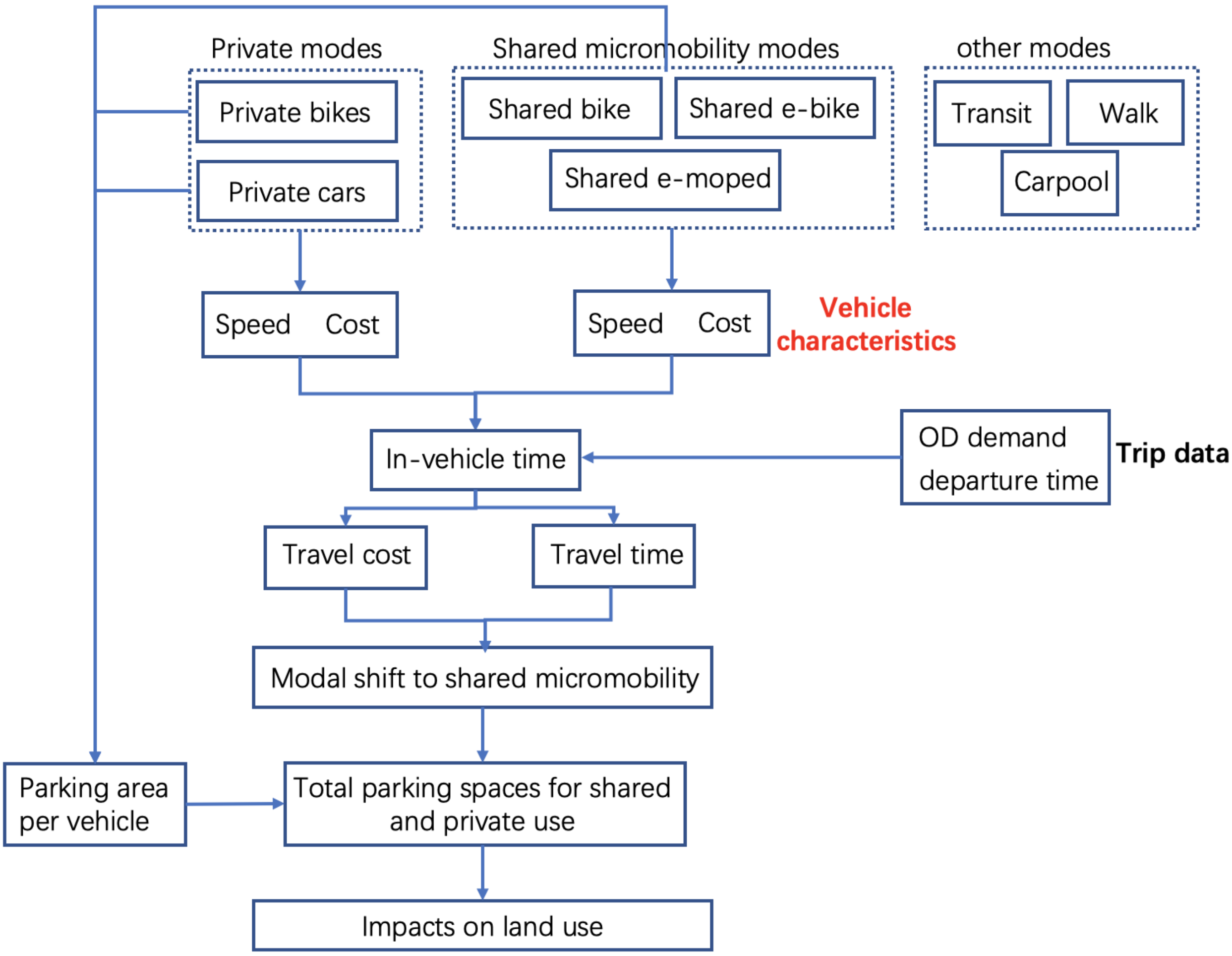

Figure 1: Model framework

The above literature review denotes that studies of shared mobility are classified into supply and demand. The impacts of shared micromobility on parking spaces originate from the modal shift from private modes to shared micromobility modes. Shared vehicles can save land space as the existing vehicles are being utilized more efficiently. A smaller fleet size that can satisfy the same travel demand for the mode will lead to less idle time. Thus, the required parking area will decrease, and more land spaces will be released. The above conclusion is valid for shared autonomous cars (Zhang et al., 2015), which is also possible for shared micromobility modes. Moreover, as the parking area per car is much larger than a micromobility vehicle, thus, a modal shift from cars to shared micromobility modes will be beneficial for saving more land space. On the other hand, a modal shift from other modes (transit, walking) is also possible. Higher demand for shared micromobility could lead to higher demand for parking spaces, which leads to more parking spaces. Nevertheless, the modal shift from private modes to shared micromobility is still crucial in how shared micromobility influences parking spaces.

Another question regarding the competitiveness of shared micromobility versus private cars is rising. As acknowledged, numerous aspects will be considered when travelers choose transport mode. Travel time and travel costs are the most essential ones among all. Several factors can affect travel cost and time, which are concluded and categorized in table 1: trip-related, supply, and external factors. Topography, user socio-demographics, and other things can affect travel time and costs. However, speed and cost of vehicle supply are the most directly related ones, which can also be used to distinguish various shared micromobility modes. The speed of shared e-micromobility vehicles is lower than but close to the speed of cars in the urban area. Also, shared e-micromobility vehicles have more advantages in certain conditions. For instance, due to congested road lanes during peak hours, travel time would be shorter than cars.

As for travel costs, shared mobility will undoubtedly cost more than private cars, and the cost gap will be more significant if the travel distance is longer. However, most trips that can be switched from cars to shared micromobility modes are intermediate-distance trips, so the cost gap will be insignificant, and shared micromobility has the potential to compete with private cars. Therefore, the speed and cost of vehicles will be the main elements in the framework, as shown in figure 1. Also, sharing attributes, weather protection, and a requirement on driving skills of modes will be considered when people choose modes, though not showing in the framework.

In the framework, directional arrows represent that the former factor can affect or decide on the latter factor. Though the supply of vehicles is the focus of this research, modeling modal split still requires internal factors of the demand side as traveler behavior will be incorporated. In this study, multiplicative multinomial logit (MNL) model with PS factor will be applied to mimic travelers choosing transport modes. More attributes will be included in utility functions (see in appendix) such as if this mode is sharing or not sharing, driving skills required or not, can carry luggage or not. Trip data and transport modes are constant input, while the specific shared micromobility mode is experimenting input. There are three types of transport modes, private modes, including private bikes and cars; shared micromobility modes, including shared bikes, e-bikes, and e-mopeds; other modes, including transit, walking, and carpool. As mentioned above, travel time and travel cost. Modeling mode split requires the attractiveness of all modes, which is often reflected by generalized travel cost (GTC). In this study, multimodal trips will not be considered, so travel time only contains in-vehicle time, excluding access time, egress time, and transfer time.

4 Simulation model

4.1 Parameter settings

Table 2 demonstrate values of cost, speed and parking area for all modes incorporated in the model. Cost and speed of privates and other modes are embedded values. Numerous papers differentiate the speed of various shared micromobility vehicles. Due to differences in investigating regions, including the built environment, user attributes, policies, etc., results of speed is distinct as well. Several studies indicated 25km/h for most shared e-micromobility and e-mopeds have higher speed than e-scooters and e-bikes in general (Yanocha & Allan, 2019; Felipe-Falgas et al., 2022; Bieliński & Ważna, 2020; Şengül & Mostofi, 2021). According to James (n.d.) and Gzaelle (n.d.), the average speed of bikes and e-bikes and 26km/h and 38km/h. However, the speed of shared bikes must be the same as private bikes, which is the built-in value. Therefore, the speed of shared e-bikes is determined by the ratio, as shown in the equation below:

Table 2: Values of parameters

Classfication	Modes	Cost (euro/km)	Speed (km/h)	Parking area (m^2/veh)
Private modes	Private bikes	0.0137	14.6214	1.5000
	Private cars	0.1900	36.6684	15.0000
Shared modes	Shared bikes (S1)	0.3283	14.6214	1.5000
	Shared e-bikes (S2)	0.6857	21.0000	1.5000
	Shared e-mopeds (S3)	0.8163	25.0000	1.5000
	Shared e-mopeds (S4)	0.8490	26.0000	1.5000
	Shared e-mopeds (S5)	0.8816	27.0000	1.5000
	Shared e-mopeds (S6)	0.9143	28.0000	1.5000
Other modes	Transit	0.2000	29.0745	
	Walk	0.0000	5.0000	
	Carpool	0.0950	30.6768	

$$(38/26) * 14.6214\, km/h \Rightarrow 21\, km/h \tag{1}$$

The speed of shared e-mopeds is hard to be determined since being constrained by the speed of other modes. It cannot exceed the speed of cars, carpool, and transit but is higher than other shared micromobility modes. Therefore, a range of values between 25km/h and 28km/h will experiment with scenarios 3 to 6 (S3, S4, S5, S6). Scenarios 1 to 2 represent shared bikes and e-bikes respectively (S1, S2).

Cost with unit euro/km depends on charging fee with unit euro/min. Charging fees of shared bikes and e-bikes are derived from Maxwell (n.d.) and Gosharing (n.d.): 0.08euro/min and 0.24euro/min. The transforming equation for shared bikes and e-bikes is as below:

$$\text{cost} = \text{charging fee}/(\text{speed of the mode}/60) \tag{2}$$

We expect that a higher cost represents a higher speed for any type of shared mobility vehicle. Assume the increase ratio of cost is the same as of speed. Thus, cost for shared e-mopeds is determined as below:

$$\text{cost of e-bike}/\text{cost of e-mopeds} = \text{speed of e-bike}/\text{speed of e-mopeds} \tag{3}$$

$$\Rightarrow \text{cost of e-mopeds} = \text{cost of e-bike} * (\text{speed of e-mopeds}/\text{speed of e-bike}) \tag{4}$$

Parking area per bike is 1.5 m^2 (Hua et al., 2020), so all micromobility modes share the same value. Area of one car equals to ten bikes (Yanocha & Allan, 2019), parking area per car is thereby 15 m^2.

4.2 Calculation approaches of parking areas

The calculating approach to parking spaces for private and shared modes is different, and assumptions for calculation are correspondingly distinct. For each scenario, sum parking area of private and shared vehicles. The sum can represent occupying land space, reflecting impacts on land use.

Private modes:
Assume all arriving vehicles during the simulation period will not depart again; in other words, all departing vehicles of the station are parked before the simulation periods. The model also assumes that all parking demand will be satisfied. Sum the number of departing vehicles of all time steps, and denote it as the initial number of parking vehicles before simulation periods. Count the number of arriving and departing vehicles and the accumulating vehicles of each station for each time step during the simulation time. The required parking space is the maximum value of accumulating vehicles for all time steps. Mathematical equations are shown below.

$$S_i = \sum_{j \in J} D_i^j \ \ \forall i \in I \tag{5}$$

$$X_i^0 = S_i + A_i^0 - D_i^0 \ \ \forall i \in I \tag{6}$$

$$X_i^j = X_i^{j-1} + A_i^j - D_i^j \ \ \forall i \in I \ \ \forall j \in J \text{ if } j \neq 0 \tag{7}$$

$$ParkingDemand_i = max(S_i, \max_{j \in J} X_i^j) \ \ \forall i \in I \tag{8}$$

$$ParkingArea_i = ParkingDemand_i * \text{area per vehicle of the mode } \forall i \in I \tag{9}$$

$I = \{1, ...i, ...I\}$ Set of stations
$J = \{1, ...j, ...J\}$ Set of timesteps
A_i^j : The number of arriving vehicles at time step j in station i
D_i^j : The number of departing vehicles at time step j in station i
X_i^j : The number of accumulating vehicles at time step j in station i
S_i : The initial number of parking vehicles before simulation periods in station i

Shared modes:
The model assumes all demand for shared modes will be satisfied, and no travelers will be rejected. Same with the calculation of private modes, count the number of arriving and departing vehicles and the accumulating vehicles of each station for each time step during the simulation time. Record the minimum and maximum value of the number of accumulating vehicles during the simulation time for each station. For any station, the absolute value of the minimum number of accumulating vehicles is the fleet size, and the difference between the maximum and minimum value is the parking demand (unit: times). Corresponding mathematical equations are as follows. Sets, departing, arriving, and accumulating variables, are the same as the calculation of private modes.

$$X_i^j = X_i^{j-1} + A_i^j - D_i^j \ \ \forall i \in I \ \ \forall j \in J \text{ if } j \neq 0 \tag{10}$$

$$X_i^0 = A_i^0 - D_i^0 \ \ \forall i \in I \tag{11}$$

$$FleetSize_i = \max(0, -\min_j X_i^j) \ \ \forall i \in I \tag{12}$$

$$ParkingDemand_i = \max(0, \max_j X_i^j - \min_j X_i^j) \ \ \forall i \in I \tag{13}$$

$$ParkingArea_i = ParkingDemand_i * \text{area per vehicle of the mode } \forall i \in I \tag{14}$$

4.3 Results

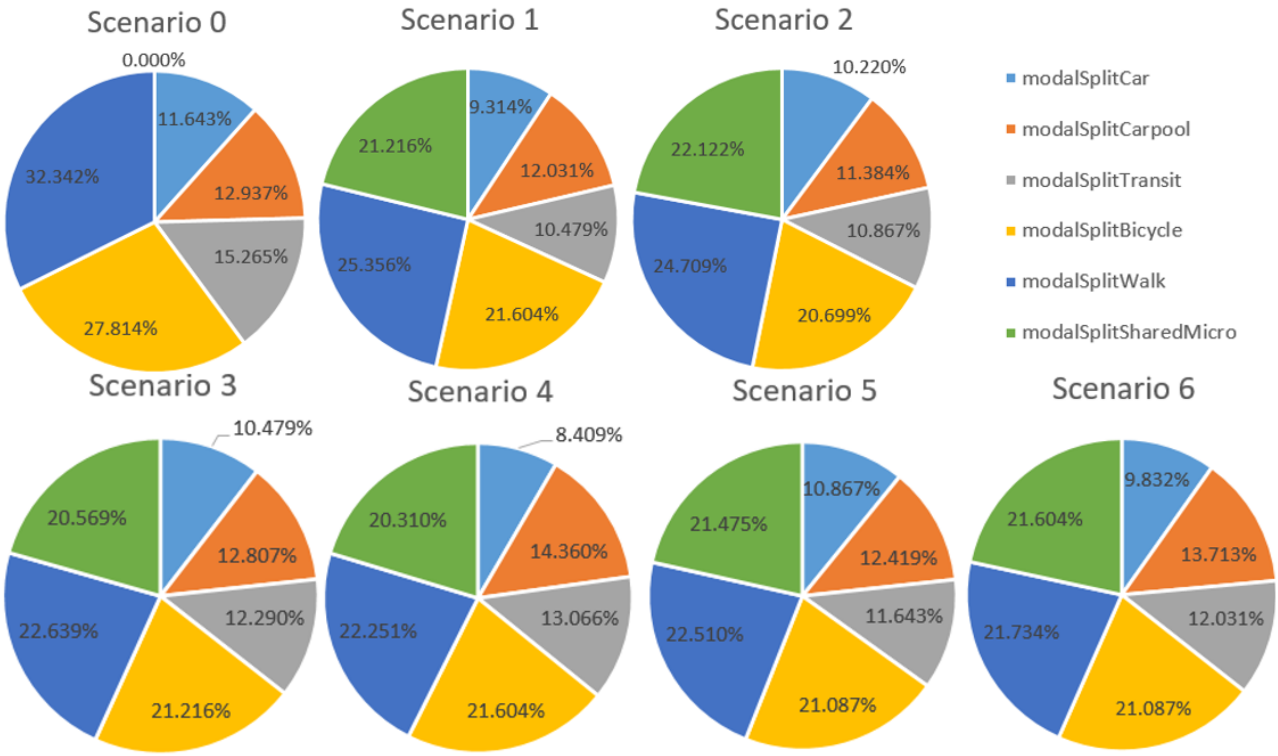

Figure 2: Modal split of seven scenarios

Table 3: Parking area of seven scenarios

Scenarios	Private bikes	Private cars	Shared vehicles	Total
0	541.5	1890.0	0.0	2431.5
1	424.5	1620.0	235.5	2280.0
2	402.0	1890.0	232.5	2524.5
3	406.5	1770.0	238.5	2415.0
4	442.5	1530.0	222.0	2194.5
5	423.0	1860.0	255.0	2538.0
6	432.0	1590.0	228.0	2250.0
Average of S3 to S6	426.0	1687.5	235.9	2349.4

Besides the six experimenting scenarios introduced above, another scenario does not incorporate any shared mode and is a reference named scenario 0. For all scenarios, the scaling sample size is 500, and the chosen seed is 3456. The number of trips is 772. All stations of shared micromobility are assumed in centroids of zones. Delft is the simulated city in this model.

Section 3 describes how modal split affects the total parking area. We expect lower splits of private cars and bikes, which is achieved as shown in figure 2. The bicycle splits of scenarios 1 to 6 are all lower than scenario 0, the same as the car splits. It represents that any shared micromobility mode can change modal split as expected. Shared e-moped in scenario 4 decreased

Table 4: Modal split of micromobility modes

Scenarios	Modal Split of Micromobility
0	27.814%
1	42.820%
2	42.820%
3	41.785%
4	41.915%
5	42.561%
6	42.691%
Average of S3 to S6	42.238%

car split to the lowest value, denoting that it is more attractive than other shared micromobility modes compared to private cars. However, the reduction in scenario 5 is the minimum. It indicates that in this model, slight differences in cost and speed of the new mode could have distinct impacts on the modal split, even though scenarios 4 and 5 represent the same mode. Correspondingly, the largest and smallest occupying area are scenarios 5 and 4 according to table 3 respectively. Therefore, the key to decreasing parking area is to reduce car split, though the difference in car split is only around 1% and 2%.

Regarding bicycle split, the differences between any experimenting scenario (S1-S6) and scenario 0 are all around 6%. Shared e-bikes can attract the most bike users, indicating that the configuration of cost and speed in scenario 2 is the most competitive compared to other shared modes. The differences in car split are all as small as around 2%. Shared micromobility modes can attract users of private bikes and change the bicycle split more significantly than the car split. However, they are not competitive when compared with private cars. Few travelers would shift modes from private cars to shared micromobility modes. Private cars can offer the fastest trips with relatively lower costs based on table 2.

Around 21% travelers choose shared micromobility modes for all experimenting scenarios (S1 to S6), reflecting the attractiveness of shared micromobility modes are similar though vehicle characteristics are various. The small gap in cost and speed would not affect the attitude toward the shared micromobility mode of travelers. Table 4 displays the sum of private bike and shared micromobility splits for seven scenarios with an average value of shared e-mopeds. Although the values of the six experimenting scenarios are similar and fluctuate between 41% and 42%, shared bikes and e-bikes could have larger potential in increasing the usage frequency of micromobility modes.

In table 3, the parking area of scenarios 1, 3, 4, and 6 are all less than scenario 0. Among these, shared e-mopeds of scenario 4 can reduce occupying land space most significantly, followed by shared bikes in scenario 1. The average value of scenarios 3 to 6 represents the average occupying spaces when introducing shared e-mopeds. It is higher than shared bikes. The uncertainty of shared e-moped regarding cost and speed leads to the belief that this mode will not be considered the best mode that can decrease parking area in general. Speed and cost among scenarios 3, 4, 5 and 6 are both slight different but total parking area between each two adjacent scenarios differ much. Area of private or shared bikes are similar for these four scenarios, area of private cars play the main role on total parking area. Scenarios 4 and 6 have relatively small area of private cars while scenarios 3 and 5 have large area of private cars. It will lead to a belief that car split in scenarios 3 and 5 could be high. How cost and speed of the new mode affect splits of other modes needs to be answered in the future. However, private cars' area in scenarios 0 and 2 are the same though these two scenarios have distinct car splits. Hence, another possible explanation regarding unreasonable parking area could be that the applied scaling sample size is not large enough so results don't reflect the reality accurately.

Therefore, the shared bike is the most beneficial mode in reducing occupying land space. Nevertheless, shared e-mopeds, on an average level, are also effective in relieving land space and reducing parking areas through utilizing vehicles. Shared e-bikes in scenario 1 can only increase parking spaces compared with scenario 0. The parking area of private cars or shared e-bikes is too large to be the same as scenario 0, which leads to the maximum parking area.

Much fewer people choose walking when introducing shared micromobility modes. Shared e-mopeds can attract the most people to shift modes from walking as the car split of scenarios 3 to 6 are all smaller than scenarios 1 and 2, though the difference is between 1% and 2%. Shared e-mopeds As for transit, the situation is exactly the opposite. Shared bikes and e-bikes can reduce the transit split lower than shared e-mopeds. Impacts on the carpool split are uncertain for different scenarios as the split could increase or decrease in comparison with scenario 0. Carpool can also be considered as a shared mode that shares rides. Thus, shared micromobility modes are less competitive when compared with carpool rather than other conventional modes.

Figure 3, 4, and 5 display the number of accumulating vehicles during simulation time of scenarios 1 to 3, respectively. Accumulating vehicles for other scenarios are not represented below but are displayed in the appendix. Each line represents a different station. For each scenario, the lowest line is station 2628 or 2614, and the highest line is station 2627. It reflects that the general usage patterns regarding arriving and departing stations are the same for any shared micromobility mode. Station 2627 is where users arrive most often, while stations 2628 and 2614 are where the most shared-micromobility users depart. Therefore, the fleet size of stations 2628 and 2614 is more extensive than any other station when implementing a shared micromobility system. Moreover, the fleet size of station 2627 can be 1 or 2, or even 0.

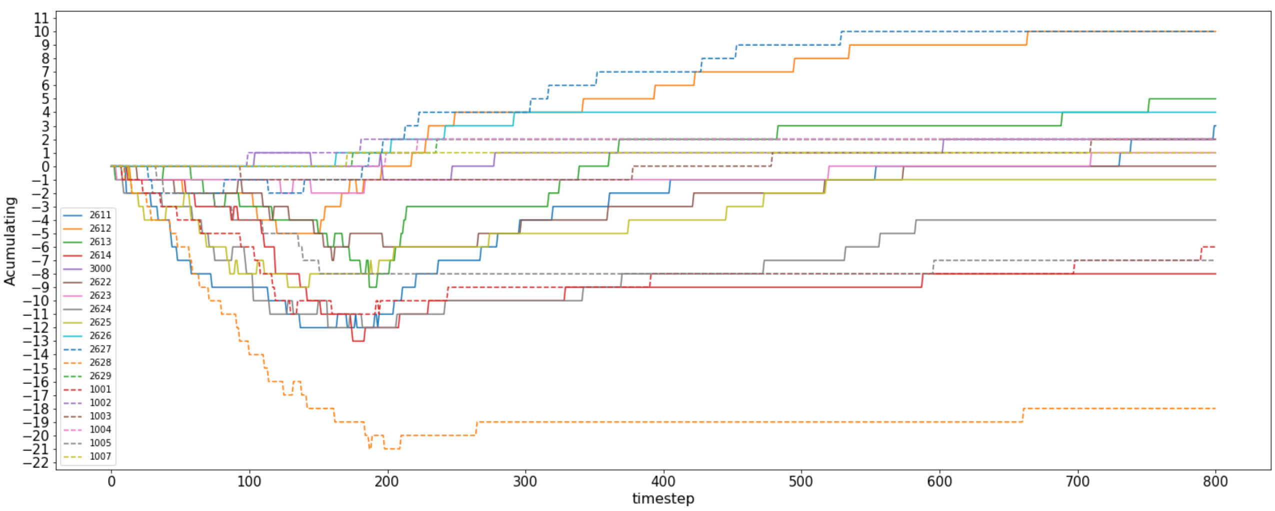

Figure 3: Accumulating vehicles of scenario 1

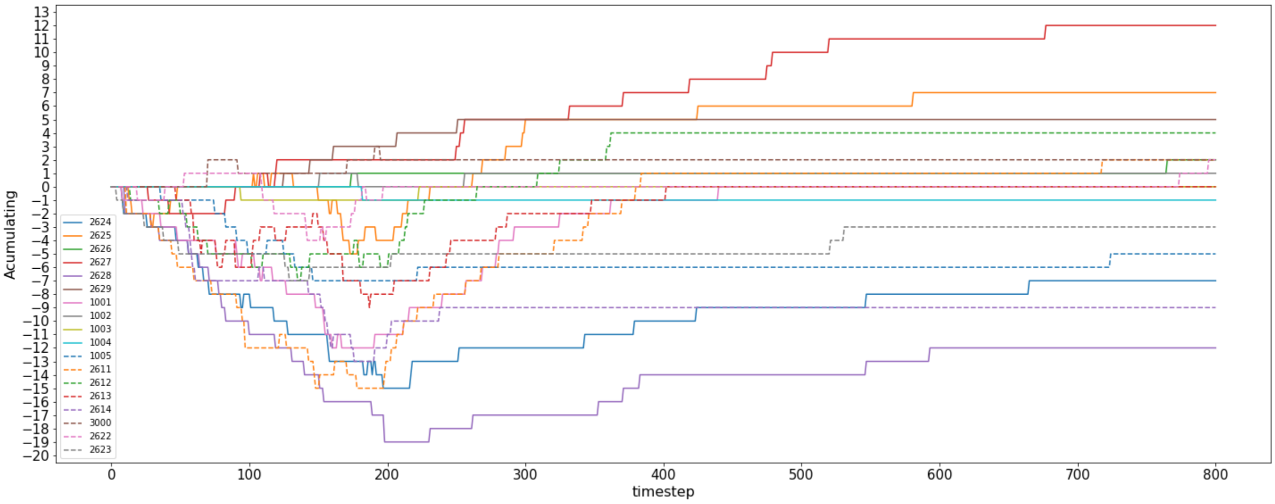

Figure 4: Accumulating vehicles of scenario 2

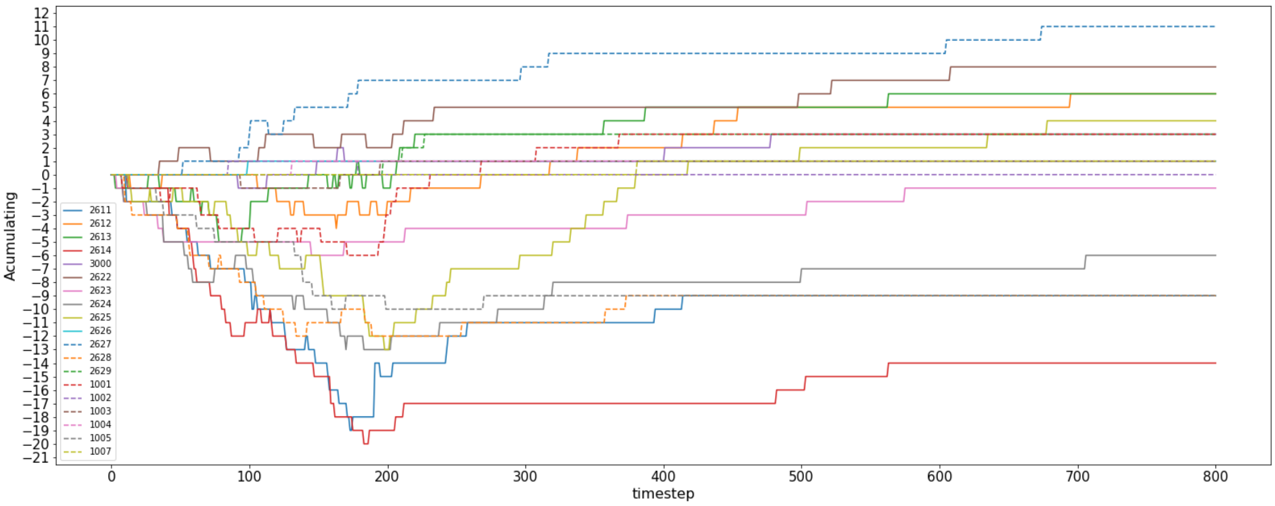

Figure 5: Accumulating vehicles of scenario 3

5 Sensitivity analysis

A sensitivity analysis on speed and cost coefficients in the utility function will be implemented to ensure the above results are accurate and the analysis is valid. Keep the scaling sample size 500 and seed number 3456, as well as other parameters, the same, and change values of cost and speed separately. When studying the cost coefficient, keep the value of speed as 14.62km/h. When studying the speed coefficient, keep the cost value as 0 euro/km. Table 5 and 6 demonstrate the results of the modal split.

The split of the shared micromobility mode should decrease as the cost increases as expectation. A new mode with higher costs will lead to a lower proportion of people choosing this mode. Nevertheless, the split increases with cost growth and reaches the highest value when the cost is 5 euro/km. And the lowest split occurs when the cost is 0. Therefore, coefficients of cost in the utility function are not appropriate (see in appendix). After checking, there are six sets of coefficients in the simulation model. Coefficients of cost are positive in two sets, which is not logical.

In general, the split of shared micromobility is rising with the increase of speed in table 6. As time is the attribute directly related to speed, the time coefficient in the utility function is found to be negative for all six sets. When the speed value increases from 0 to 21, the split of shared micromobility is close to the bicycle split. However, when speed becomes 50 or 100, the split of shared micromobility still fluctuates between 21% and 23%. Additionally, there are still 16.95% of travelers choose shared micromobility when the speed is as low as 1km/h. Thus, the time coefficient is not sensitive enough, especially for extremely low or high speed values.

Table 5: Modal split for sensitivity analysis on cost coefficient

cost (euro/km)	speed (km/h)	Car	Carpool	Transit	Bicycle	Walk	ShareMicro
0.00	14.62	9.70%	13.32%	13.32%	21.35%	23.29%	19.02%
0.30	14.62	8.28%	12.81%	10.09%	22.25%	25.61%	20.96%
0.60	14.62	7.89%	12.42%	10.74%	23.03%	25.23%	20.70%
0.90	14.62	8.15%	12.03%	11.25%	22.90%	24.97%	20.70%
1.20	14.62	8.15%	12.29%	10.87%	22.64%	25.10%	20.96%
5.00	14.62	10.22%	12.03%	12.29%	21.86%	20.96%	22.64%
10.00	14.62	9.83%	12.81%	11.00%	21.09%	22.38%	22.90%
50.00	14.62	9.96%	12.42%	10.09%	24.84%	21.47%	21.22%

Table 6: Modal split for sensitivity analysis on speed coefficient

cost (euro/km)	speed (km/h)	Car	Carpool	Transit	Bicycle	Walk	ShareMicro
0.00	1.00	11.64%	12.42%	12.94%	21.35%	24.71%	16.95%
0.00	7.00	9.06%	14.36%	11.90%	21.86%	24.45%	18.37%
0.00	14.62	9.70%	13.32%	13.32%	21.35%	23.29%	19.02%
0.00	21.00	9.06%	13.84%	10.22%	21.73%	24.19%	20.96%
0.00	28.00	9.31%	13.07%	9.83%	20.57%	24.97%	22.25%
0.00	50.00	9.57%	13.84%	10.22%	21.60%	23.54%	21.22%
0.00	100.00	9.96%	12.68%	10.87%	20.57%	22.64%	23.29%

6 Conclusion

Two central problems in the simulation model are discovered during the studying process. When checking trip data carefully, almost all travelers would go back and forth. They repeat passing nodes that are already passed. Moreover, some travelers arrived at their destinations but still keep moving forward to another node. Besides, travelers often take detours even when the trip distance is short or the mode is walking, which means no congestion. The other problem is that the new mode cannot combine with other modes and be part of multimodal trips in the multimodal network. Even for the built-in mode, shared autonomous vehicles, the mixed modal split representing multimodal trips is also 0. Hence, the multimodal network is not applied in this study, and two roles of shared micromobility mentioned in Introduction are not modeled. Results on the modal split could be relatively off due to the problem concerning trip data.

Main findings:
This study completed a literature review on shared micromobility and summarized and categorized the main influential factors which affect parking spaces. Also, four literature gaps are found to the author's best knowledge, and determined vehicle supply is the focus of this study. Calculation approaches on parking spaces for private modes and shared modes are proposed. Moreover, changed values of cost and speed of new modes to represent different shared micromobility modes and applied calculation approaches for each scenario. The total parking area of cars, bikes, and the shared micromobility mode can be derived, and the impacts of different shared micromobility modes are obtained. At last, a sensitivity analysis on coefficients of cost and speed in utility functions is carried out.

A shared bike is the most effective and stable mode that can reduce parking area, relieving the most land space. Furthermore, the reduction of car split compared to scenario 0 is the most crucial element for impacts on parking spaces, and even a 1% reduction could have a great influence. Scenario 4, with a cost equal to 0.8490 euro/km and speed equal to 26km/h, can decrease car split to the lowest value, so the total parking area is the minimum. Another thing can also be reflected that, scenarios 4 and 5 have the smallest and largest parking area though both represent the introduction of shared e-mopeds, but produced the best and the worst result, respectively. The small gap in cost and speed can make significant differences in the parking area. It could also be related to coefficients in utility functions or stochasticity in the model. In addition, the attractiveness of all shared micromobility modes is similar compared to private bikes, as the bicycle splits are similar for all experimenting scenarios (S1-S6). The bicycle split decreased to the similar value when any shared micromobility was included.

The sensitivity analysis shows that the coefficients of speed and cost in utility functions are inappropriate. Some positive coefficients of cost could make the modal split extremely unreasonable. Speed coefficients are not sensitive enough to model the difference on modal split when the speed value is changed. The conclusion on impacts could be inaccurate due to values of speed and cost coefficients, as well as the "back and forth" problem. However, the calculation approaches of parking area for both private and shared modes can still be applied when these problem are solved.

Limitation:
This study uses cost and speed to differentiate various shared modes. Other vehicle characteristics, such as battery range and occupancy, are not considered. Multi-person trips would prefer shared e-moped as two people can occupy it. Similarly, Shared e-mopeds are more favorable than other micromobility modes because of the more extensive battery range for longer-distance trips. Moreover, the availability of shared vehicles needs to be considered. The model assumes that each trip will be satisfied, which is unrealistic. In real life, the demand of travelers cannot always be satisfied as the dynamic imbalance of supply and demand involves spatial and temporal dimensions. Besides, battery range could be essential in availability since electric vehicles must be charged at stations. If the battery range is long, the charging periods of vehicles will be shorter. The lack of modeling occupancy, battery range, and availability could significantly affect results on modal split, which means that less people would choose shared modes and impacts on relieving land space are less positive. It is something to be improved in the future.

Another missing thing in the model is the parking fee for private cars. As the parking fee is high in Europe, especially the Netherlands, the absence of a parking fee could make a difference in travel costs, as well as choices of transport modes.

As aforementioned, travel time is one of the key factors which decide mode choice besides travel cost. This study only takes in-vehicle time into account, while access and egress time is not considered. Access and egress time can only be derived based on the exact positions of stations. The current simulation model cannot model a detailed network in a spatial dimension. Stations of shared micromobility and transit are assumed in centroids of zones. Access time to mode and egress time from modes are offered to be changed in this model. However, it is a constant parameter in one simulation, which cannot distinguish different trips. In the aim of modeling travel time better, it should be improved in the future, especially for multimodal trips considering transfer time.

Six scenarios are designed to model vehicle characteristics of shared micromobility vehicles. Values of cost and speed are given based on information on the websites of shared mobility companies and related research. Higher-speed modes are assumed to have higher costs. However, it is still a question if these values are reasonable. Also, the cost of shared bikes is 30 times of private bikes while shared e-bikes cost as high as 60 times of private bikes. Differences in cost or speed between modes could be off a reality since some of values are determined based on ratios. In addition, a smaller scaling size factor should be applied to reflect reality more accurately and avoid aggregated results on choice modeling.

Reflection Statement

This study completed a literature review on shared micromobility and summarized and categorized the main influential factors which affect parking spaces. Also, four literature gaps are found to the author's best knowledge, and determined vehicle supply is the focus of this study. Calculation approaches on parking spaces for private modes and shared modes are proposed. Moreover, changed values of cost and speed of new modes to represent different shared micromobility modes and applied calculation approaches for each scenario. The total parking area of cars, bikes, and the shared micromobility mode can be derived, and the impacts of different shared micromobility modes are obtained. At last, a sensitivity analysis on coefficients of cost and speed in utility functions is carried out.

During the studying process, I learned that self-motivation is important when doing research. Understanding my interest and determining the research topic is a long way to go. The research scope cannot be too broad. Also, the original research topic cannot be completed for realistic reasons. Learning to change studying topics and switching to a feasible direction in time is essential. Moreover, finding an appropriate methodology for a topic requires considering the efficiency and accuracy of all alternatives.

The simulation model in this study is developed by Koen de Clerq. Although I didn't develop one independently, I spent much time understanding the code. Now I am familiar with the simulation model structure and the necessary steps. If I need to develop my own simulation model, I will know what is required to be included, what factors to consider, and what steps to follow.

The study discovered two central problems in the simulation model: back and forth, zero mixed modal splits of future modes for multimodal trips. They can be identified in trip data. So another thing I learned is to check results carefully before going to the next research step. Writing down critical bullet points and briefly analysing obtained results help follow studies.

Appendix

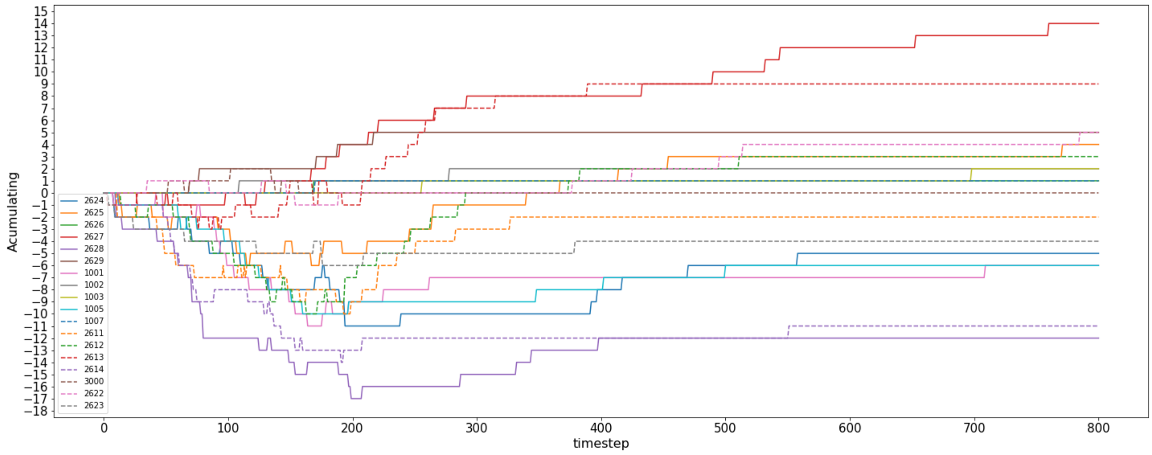

Figure 6: Accumulating vehicles of scenario 4

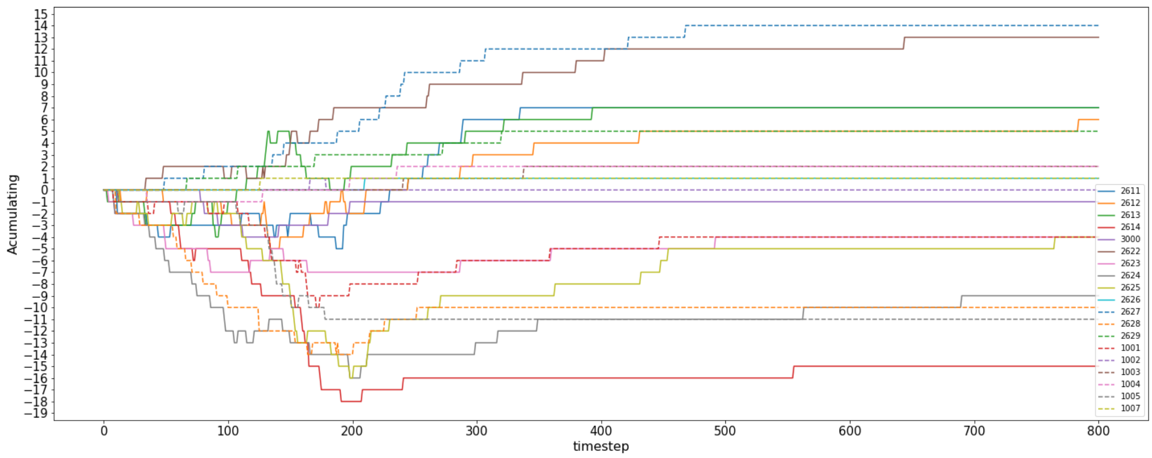

Figure 7: Accumulating vehicles of scenario 5

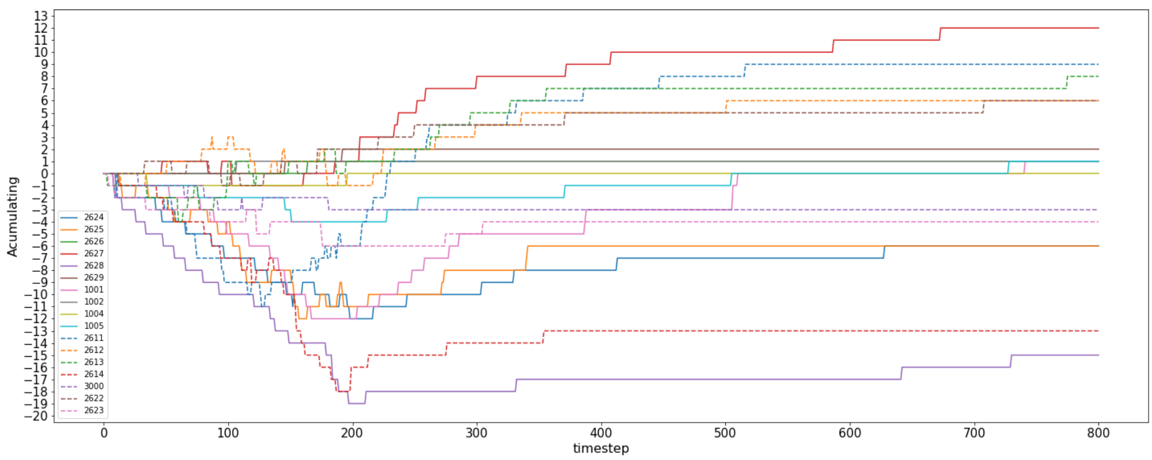

Figure 8: Accumulating vehicles of scenario 6

utility = B[0] * cost + B[1] * time * 60 + distance * (B[2] * 0 + B[3] * drivingTask + B[4] * skills + B[5] * weatherProtection + B[6] * luggage + B[7] * shared + B[8] * availability + B[9] * reservation + B[10] * active + B[11] * accessible)

Betas = [[0.0193, -0.0208, 0.3, -0.571, -0.16, -1.07, -1.08, -0.611, -1.87, -0.733, 0.74, -0.671], [-0.0267, -0.0439, 0.29, -0.0884, 2.17, -0.402, -1.39, -2.01, -3.96, -1.74, -0.00596, -2.58], [-0.0343, -0.0207, -0.5, -0.855, 1.44, -0.284, -0.0653, -1.25, -1.44, -0.292, 0.314, -1.25], [0.0229, -0.0243, -0.42, -1.21, 2.22, -0.781, -0.719, -3.8, -8.28, 0.313, 0.58, -3.49], [-0.0123, -0.036, -0.22, -0.129, -2.81, -1.22, -0.952, 1.3, -0.24, 1.79, 1.22, 1.41], [-0.0806, -0.0218, -0.42, -1.2, 1.52, -0.0638, -0.248, -1.43, -2.46, 0.672, 0.314, -1.94]]

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