Analysing the Effects of Adding Shared Electric Bicycles as a New Mode on the Modal Split of Multimodal Trips between Delft and Rotterdam Using an Unlabelled Multimodal Supernetwork

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SHORT SUMMARY
Assessing to what extent new modes will change modal split is difficult, since revealed preference data is not available yet to estimate models. To address this, an unlabelled multimodal supernetwork is developed in which mode and route choice are simultaneously modelled. The model has been estimated based on data of existing modes and can be used to assess the impact of any new mode. We applied the model to analyse the effects of shared e-bicycles on one Origin-Destination pair between Delft and Rotterdam. The main scientific contribution of this paper is that it successfully demonstrates how an unlabelled multimodal supernetwork can be used to analyse the effects of shared e-bicycles on the modal split between Delft and Rotterdam. The results show that the modal share of shared e-bicycles is 35.3-40.5% for unimodal trips and occur in 36.2-46.3% of multimodal trips, indicating that shared e-bicycles can significantly change the modal split.

Keywords: agent-based modelling; multimodal; shared e-bicycles; supernetwork; unlabelled mode choice

Word count: 2496

1. INTRODUCTION

Several mobility systems, ranging from shared electric bicycles to autonomous vehicles, have been developed. These new mobility systems could change the way our societies function in terms of sustainability, equity, accessibility, and safety (Fagnant & Kockelman, 2015; Milakis et al., 2017; Shaheen et al., 2019).

Researching how new modes affect mode choice is difficult since revealed data of the potential users using these new mobility systems are not available yet, so mode specific parameters cannot be estimated. In our previous research, this challenge has been addressed by developing an abstract, or unlabelled, mode modelling approach to assess the modal share of any new mode and unimodal trips (De Clercq et al., 2022). The unlabelled mode modelling approach was first introduced by Quandt & Baumal and describes a method to formulate a discrete choice model by describing the utility of each mode with the same mode attributes for each mode and by leaving out mode-specific constants and parameters (Quandt & Baumal, 1966). In our previous research (De Clercq et al., 2022), it was shown that any new mode can be modelled using the unlabelled mode modelling approach as long as the new mode can be described as a (new) combination of existing attributes of which the relative importance can be estimated based on revealed preference data. In those cases, the utility function of the new mode can be defined and thus the new mode can be added as an option in the choice set of a discrete choice model. However, a shortfall of this approach is that it does not yet cover multimodal trips.

New modes, such in our case shared electric bicycles, will be often used for the the first- and/or last-mile parts of a trip and will only available at certain locations (e.g., mobility hubs) (Van Eck et al., 2014). Therefore, to analyse new transport modes, it will be often necessary to analyse their use in a multimodal setting. This can be done by developing a multimodal supernetwork which can model multimodal trips without the need to predefine the combinations of mobility systems and where mode and route choice happens simultaneously (Liao, 2016; Van Eck et al., 2014; Vo et al., 2021). These models only need to know where people are allowed to switch modes (e.g., where the mobility hubs are located).

In our study (De Clercq et al., 2023), we developed such a supernetwork approach to assess the impact of new mobility systems. Following the same logic as with the previously mentioned unlabelled discrete choice model (De Clercq et al., 2022), in our supernetwork, one can define the new mobility system by describing it in terms of a broad set of mode attributes but without any mode-specific constants, and add that mode as a new 'layer' in the supernetwork. So far, the model has only been applied to theoretical simple networks and a fictive multimodal version of the Sioux Falls network to demonstrate and verify the method. In this paper, we applied the model in a more realistic case situation. We focus on the introduction of shared electric bicycles on one example Origin-Destination (OD)-pair between Delft and Rotterdam because cycling is a dominant mode of transport in the Netherlands and electric bicycles are becoming increasingly popular (Sun et al., 2020).

This paper contributes to the existing literature by demonstrating how an agent-based multimodal supernetwork-based traffic assignment model with unlabelled modes that takes into account mode and route choice simultaneously can be applied in a real use-case to gain insight into the influence of shared electric bicycles on a specific OD-pair between Delft and Rotterdam, including the use in the first and last-mile parts of a trip. Knowledge gaps and possible future research directions to research the effects of new modes on the modal split of urban areas are identified and discussed as well.

2. METHODOLOGY

Figure 1 summarizes the supernetwork approach that has been applied in this paper. Trip generation and distribution are considered exogenous. Mode and route choice are calculated simultaneously based on the resistance per edge. Subsequently, per timestep, trips are assigned to the supernetwork using a mesoscopic dynamic traffic assignment approach. The assignment model with the supernetwork is set up using Python 3.10.2 and the NetworkX package (Hagberg et al., 2008). Below, the main elements of the assignment model are described. For an extensive description of the network definition, the combined mode and route choice model and the network loading model, refer to (De Clercq et al., 2023).

The supernetwork consists of one layer for each mode. Edges represent aggregated road segments with generalized resistance (i.e., disutility), transit segments (representing aggregated transit lines) and dummy transition edges from and to a neutral layer (representing transfer resistance). The transport mode edges have a length and a number of attributes (representing the mode and link attributes), where for modes using the road network the 'time' attribute can change with the use of the edge (i.e., the flow).

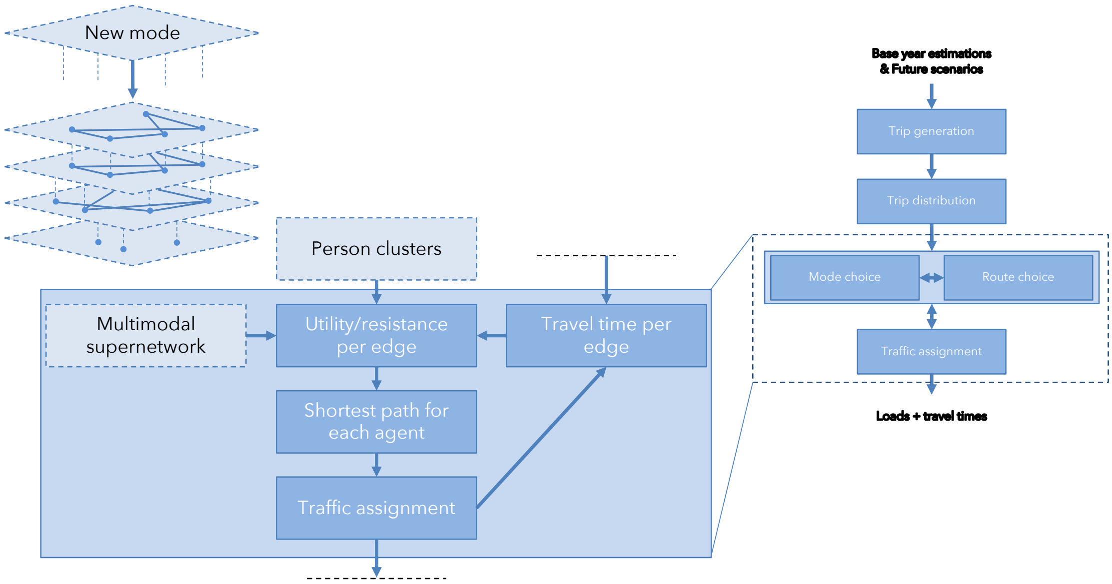

Figure 1: General layout of multimodal supernetwork (De Clercq et al., 2023)

Twelve mode attribute assumptions (times mode attribute parameters, see Table 3) have been used to define the resistance in the edges for all modes: Initial cost (€); Cost/trip (€); Time (min); Driving task (-); Skills (-) (i.e., driver's license); Weather protection (-); Luggage (-); Shared (-); Availability (-); Reservation (-); Active (-); Accessible (-). The mode attribute assumptions per mode are shown in Table 1.

Table 1: Mode attribute assumptions

Mode attribute	Addable*	Source and determination
Initial cost (€)	Yes	Car, transit, cycle, walk = 0
Cost/trip (€)	Yes	Car = €0.19 per km; transit = 0.20 per km; walk = 0; bicycle = €100 purchase costs, with 4 trips per day for 5 years
Time (min)	Yes	Car, transit, bicycle and walk from Google Maps (*Travel times Google Maps*, n.d.)
Driving task (-)	No	Car, bicycle = 1; transit, walk = 0
Skills (-) (i.e., driver's license)	No	Car = 1; transit, bicycle, walk = 0
Weather protection (-)	No	Car, transit = 1; bicycle, walk = 0
Luggage (-)	No	Car = 1; transit = 0.5; bicycle, walk = 0
Shared (-)	No	Car, bicycle, walk = 0; transit = 1
Availability (-)	No	Car = 1; transit = 0.5; bicycle = 1, walk = 1
Reservation (-)	No	Car, bicycle, walk = 1; transit = 0
Active (-)	No	Car, transit = 0; bicycle, walk = 1
Accessible (-)	No	Transit = 1; Car, bicycle, walk = 0

*Addable and non-addable attributes are implemented differently in the edge/route resistance calculations (see Eq. 1 and Eq. 2).

When agents want to switch modes, the resistance in the considered route also contains the time it takes to disembark from the mode, and embark to the mode (see Table 2) and the 'initial cost' of a mode (see Table 1). The times in these edges are multiplied by 3 to represent the extra mental effort it takes for users to switch modes and wait for the next mode (Wardman, 2004).

Table 2: Assumed time to switch modes, multiplied by 3 to model extra mental effort for switching mode, based on (Wardman, 2004)

Mode	Neutral to mode	Mode to neutral
Car	5 min (get in car)	2 min (parking)
Transit (BTM)	7.5 min (average waiting time, ass. freq.: 15 min)	5 min
Bicycle	1 min (get on bike)	1 min (parking)
Walk	0 min	0 min

The total resistance per route is defined as the sum of the edge resistances. Edge resistances are the sum of a series of products of mode attributes and the valuations of these attributes by users. For the modelling approach, homogenous groups of users are combined in clusters. There are two categories of mode attributes; one category which is addable over the route regardless of the length of each edge and the length of the route (e.g., travel time, costs) (see Eq. 1) and one category which is not addable over the route. The attributes within this last category need to be weighted with the length of each edge within the route to come to a weighted average value for those attributes (e.g., weather protection on 70% of the total length of the route) (see Eq. 2). These two edge resistance calculations are combined in Eq. 3, where the resistances of all edges in one route are summed up and divided by the length of that route to get the ratio of the mode attributes of each edge respective to their share in the total route. A multinomial logit model (MNL) (Ortuzar & Willumsen, 2011) with en-route route choice is used to determine the mode/route choice based on the route resistance. IIA (Independence of Irrelevant Alternatives) is assumed for all modes in this study.

$$E_{addable,i,t,n} = \sum_1^k \beta_n \chi_{k,i,t}, \quad \forall k \in K \qquad \text{Eq. 1}$$

$$E_{non-addable,i,t,n} = len_i * \sum_1^m \beta_n \chi_{m,i,t}, \quad \forall m \in M \qquad \text{Eq. 2}$$

$$U_{r,t,n} = \sum_{i \in I} E_{addable,i,t,n} + \frac{\sum_{i \in I} E_{non-addable,i,t,n}}{L} \qquad \text{Eq. 3}$$

where;

U = route resistance [-];
$E_{addable}$ = edge resistance addable component [-];
$E_{non-addable}$ = edge resistance non-addable component [-];
β = cluster valuation of mode attribute [-];
χ = value of mode attribute [-];
len = length of edge [km];
L = length of route [km];

n = cluster index [-];
i = edge index of edges within route [-];
k = addable mode attribute index [-];
m = non-addable mode attribute index [-];
t = time index [-];
r = route index [-];

I = set of edges within mode layers in route r;
K = set of addable mode attributes (e.g., travel time); and
M = set of non-addable mode attributes (e.g., weather protection).

The valuation (i.e., observed preferences for travellers for attributes) of the attributes have been estimated using a large-scale trip survey in the Netherlands (CBS, 2017) for the year 2017. The dataset contains personal, trip, and mode information. It contains five main transport modes: car, carpool, transit (BTM), bicycle, and walk. This dataset is further enriched with the mode attributes (see Table 1). Further more, clusters of travelers with similar characteristics have been identified, using k-means clustering and the elbow method to define the optimal number of clusters for the trips. The estimated valuations for the six clusters are shown in Table 3. Note that some parameters have different signs per cluster. This can be explained by considering that some clusters value certain traits positively (e.g., higher costs are a status symbol) and other clusters value certain traits negatively (e.g., higher costs make a mode less affordable). Because these attributes capture almost all aspects that determine mode and route choice, mode specific constants are no longer needed. The valuations of the attributes (i.e., betas) are also no longer mode-specific and therewith transferable to new modes.

Table 3: Mode attribute valuations per cluster (De Clercq et al., 2022)

Cluster	*1*	*2*	*3*	*4*	*5*	*6*
(Initial) Cost	0.0193	-0.0267	-0.0343	0.0229	-0.0123	-0.0806
Time	-0.0208	-0.0439	-0.0207	-0.0243	-0.036	-0.0218
Driving task	-0.571	-0.0884	-0.855	-1.21	-0.129	-1.2
Skills	-0.16	2.17	1.44	2.22	-2.81	1.52
Weather protection	-1.07	-0.402	-0.284	-0.781	-1.22	-0.0638
Luggage	-1.08	-1.39	-0.0653	-0.719	-0.952	-0.248
Shared	-0.611	-2.01	-1.25	-3.8	1.3	-1.43
Availability	-1.87	-3.96	-1.44	-8.28	-0.24	-2.46
Reservation	-0.733	-1.74	-0.292	0.313	1.79	0.672
Active	0.74	-0.00596	0.314	0.58	1.22	0.314
Accessible	-0.671	-2.58	-1.25	-3.49	1.41	-1.94

Case-study: Delft to Rotterdam

Figure 2 visualizes the network with first-mile, main, and last-mile edges for an example OD-relation between Delft and Rotterdam. Nodes depict centroids and mobility hubs (the network definition does not contain centroid feeders). First- and last-mile edges have multiple modes. The origin and the destinations are indicated using O and D respectively. Figure 3 gives a supernetwork representation of this network with five modes for which the model has been estimated (the reference case) and an added sixth mode shared e-bicycles (for the 'new mode' alternative). The network contains transition links between modes through a neutral layer. Note that when switching mode, an agent always needs to leave the mode, enter the neutral layer, and enter the new mode. The possible transfers on certain locations (circles) between modes are depicted with the vertical dashed lines. One example multimodal route is visualized in yellow, where the bicycle is used to cycle from the centroid (O, Delft) to the station, transit is used as main mode and walking is used for the last-mile to the destination (D, Rotterdam).

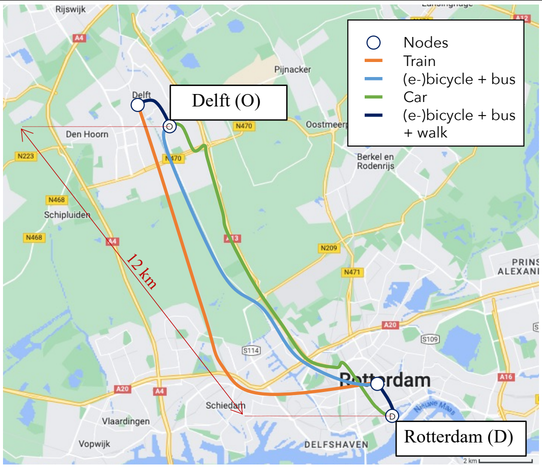

Figure 2: OD relation between Delft and Rotterdam.

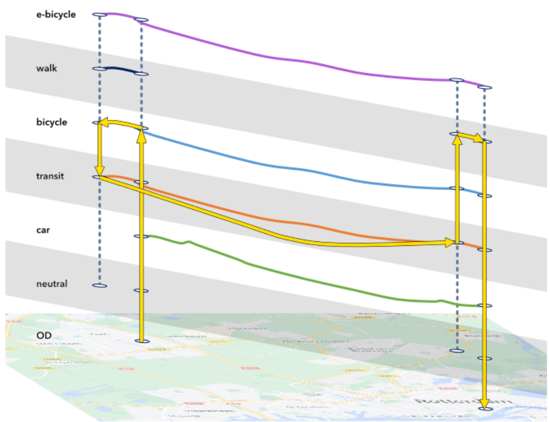

Figure 3: Supernetwork of the route between Delft and Rotterdam

The implementation of shared electric bicycles can come with different variants for initial costs, speed, generalized transit times from the neutral layer to shared e-bicycles and vice versa. These variants are described in Table 4. The possible combinations (81) of these attribute values form scenarios. These scenarios are simulated to analyse the effects of a different level of service of shared electric bikes on the modal split and travel times.

Table 4: Attribute values

Nr.	Attribute	Pricing policy
1	Initial cost shared electric step [€]	3.2 – 4.0 – 4.8
2	Speed [km/h]	20 – 25 - 30
3	Neutral to e-bike [min]	2.4 – 3.0 – 3.6
4	E-bike to neutral [min]	1.6 – 2.0 – 2.4
5	Network [-]	With/without e-bicycles

Simulation

For the simulation, the earlier identified six clusters of travelers are used; 166 trips for each cluster are simulated. A timestep of 1/100 hours (=36 sec) is used. This time step is chosen such that an agent will spend at least two timesteps on the shortest link (1.8 km) considering the highest free flow speed in this model (90 km/h). The simulated time period in the model is 4 hours representing a morning peak hour from 6 am to 10 am. The same seed number is used in all simulations to be able to compare different scenarios. The number of transfers between modes in the multimodal networks is limited to 2 (first-mile → main → and last-mile). Since transit is modelled in one layer and contains all bus, tram, metro (BTM) transit, this is assumed to be realistic.

3. RESULTS AND DISCUSSION

The results of the simulations, including sensitivity analysis results between brackets, are shown in Table 5-7. It can be observed that the modal share of shared e-bicycles ranges between 35.3 and 40.5% in unimodal trips and occurs in 36.2-46.3% of the multimodal trips, indicating that shared e-bicycles can significantly change the modal split between Delft and Rotterdam, reducing mainly the modal share of cars, cycling, and, to a lesser extent, transit and walking. When looking at the total distance travelled per mode for all scenarios, it is interesting to point out that walking is used at least in 41.7% of the multimodal trips but amounts to only a maximum of 0.6% of all distance travelled. This indicates that walking occurs for first- and last-mile as would be expected. The average travel time changes depending on the configuration of shared e-bicycles, indicating that travel time can be improved by introducing shared e-bicycles but depend on the level of service that shared e-bicycles have when they are introduced on the roads.

Table 5: Modal split (trips) with and without shared e-bicycle, including sensitivity analysis results between brackets

	Modal split [%]					
	Car	**Transit**	**Bicycle**	**Walk**	**E-bicycle**	**Multimodal**
No e-bicycles	45,4	0,8	45,8	0,0	-	8,0
E-bicycles	28,2 [25,5 - 30,4]	0,5 [0,2 - 0,5]	25,3 [23,4 - 25,9]	0,0 [0,0 - 0,0]	40,5 [35,3 - 40,5]	5,5 [5,1 - 5,8]
	Modal split of multimodal trips [%]*					
	Car	**Transit**	**Bicycle**	**Walk**	**E-bicycle**	
No e-bicycles	0,0	60,6	89,0	60,2	-	
E-bicycles	0,0 [0,0 - 0,0]	37,6 [28,6 - 37,6]	75,8 [67,9 - 75,8]	51,7 [41,7 - 51,7]	44,0 [36,2 - 46,3]	

*The modal split of mixed trips amounts to more than 100% since multiple modes can occur in one single trip. The numbers can be interpreted as the percentage of the mixed trips that contain a certain mode.

Table 6: Modal split (distance) with and without shared e-bicycles, including sensitivity results between brackets

	Modal split [% of distance]					
	Car	**Transit**	**Bicycle**	**Walk**	**E-bicycle**	**Multimodal**
No e-bicycles	43,6	0,9	46,6	0,0	-	8,8
E-bicycles	26,9 [24,2 - 28,9]	0,6 [0,3 - 0,7]	25,6 [23,6 - 29,6]	0,0 [0,0 - 0,0]	41,0 [35,7 - 45,2]	6,0 [5,5 - 7,7]
	Modal split of multimodal trips [% of distance]					
	Car	**Transit**	**Bicycle**	**Walk**	**E-bicycle**	
No e-bicycles	0,0	3,1	5,1	0,6	-	
E-bicycles	0,0 [0,0 - 0,0]	1,3 [0,7 - 1,6]	2,5 [2,1 - 3,8]	0,4 [0,3 - 0,5]	1,8 [1,5 - 2,4]	

Table 7: Average speed, distance, and duration with and without shared e-bicycles, including sensitivity analysis results between brackets

	Average speed [km/hr]	**Average distance [km]**	**Average duration [min]**
No e-bicycles	23,64	15,40	43
E-bicycles	24,01 [22,09 - 25,99]	15,56 [15,52 - 15,61]	41 [38 - 45]

The results in this study are plausible in the sense that the e-bicycle mainly replaces car and bike trips. This is in line with the findings in Sun et al. (2020). They used a longitudinal dataset from the Netherlands Mobility Panel to analyze the modal shift effects of people who bought an e-bicycle. However, the potential modal share of shared e-bicycles is slightly higher than the study of Sun et al (2020) shows. For trips of about 15 kilometres, they found a modal share of 33-36%. This might be explained by the relatively high share of normal bicycles in the reference situation for this specific origin-destination pair and the fact that a multinomial logit model is used to determine the next node for each agent, which does not account for overlap (‘red/blue-bus paradox’).

4. CONCLUSIONS AND RECOMMENDATIONS

This study successfully demonstrated how an agent-based unlabelled multimodal supernetwork-based traffic assignment model can be used to assess the effects of new modes such as shared electric bicycles on the modal split for an example origin-destination pair Delft- Rotterdam. This is done by using a supernetwork framework, where each available mode is modelled as a specific layer within this supernetwork with nodes and edges, where the edges' resistances are described by a set of attributes without an alternative-specific constant. The mode-specific layers are interconnected to a neutral layer with edges representing transfer resistances, also described with a set of attributes. The unlabelled approach, i.e., without mode specific parameters and constants, makes it possible to add any new mode.

The results show plausible modal-shift effects from cars and bicycles to shared electric bicycles. However, the absolute modal share seems slightly overestimated because overlap is not considered. To account for overlap in routes (and similar modes), it is recommended to explore grouping layers of similar modes and overlapping routes into one 'nest' by using a path-overlap factor. A path size correction logit model (PSCL) in combination with a multiplicative MNL is expected to work well on real networks (Bovy et al., 2008; Smits et al., 2018). PSCL models exist, for transit only, based on the shared number of transfer nodes, edges and travel times, which have higher accuracy for transit, but these models cannot be applied on car transport (Dixit et al., 2021). Since both transit and car modes are used, this method is not trivial to implement on a multimodal supernetwork.

The modular approach of this supernetwork allows for further explorations of other new modes, more scenarios, and other network configurations. Recommended options to explore further are to include other new modes, pricing policies, adding a time-based transit schedule, and changing the availabilities and stops of transit or other modes. Further, no disruptions (e.g., weather conditions, accidents) are analyzed in this study yet. Disruptions could be implemented by temporarily increasing the edge resistance in some places. This could be an approach to give insight into how a new mode changes the travel time reliability of a system. Finally, it is recommended to integrate this multimodal supernetwork in a land-use-transport interaction model to see how higher-order aspects, such as activity patterns, change over the years as a result of the introduction of new transport modes.

ACKNOWLEDGEMENTS

This research is part of the project SUMMALab which is supported by the research program Sustainable Living Labs from the Dutch Research Council (NWO) under Grant 439.18.460 B. The authors declare that there is no conflict of interest.

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