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An Activity Based integrated approach to model impacts of parking, hubs and new mobility concepts

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Abstract

Travel demand for the Metropolitan region Rotterdam - The Hague is predicted using a novel tool chain. Non-classical tools are required to cope with the situation where parking supply is reduced, hubs for trip chaining are made operational and people start to use MaaS including new mobility concepts. An activity based travel plan predictor is combined with a dedicated *access-egress* model and assignment models. Because the activity based model and *access-egress* model simulate individuals, they can deal with mode switches at hubs while considering constraints with respect to vehicle ownership, mode availability in the tour, locations where vehicles should be returned and mode availability. Parking capacities, hub and new mobility concepts are included in the assignment models to generated level-of-service matrices that are input to the other models. The tool chain setup, the methods applied, the datasets used and first results are discussed. The new integrated activity based approach proved to be better suited to model impacts of parking, hubs and new mobility concepts than the standard aggregated modelling approach. The results for the base year look promising because they closely resemble observed schedules and the elasticities are within the recommended ranges mentioned in literature.

Keywords: travel behaviour; activity based modelling; travel mode; MaaS

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1. Introduction

1.1. Objective - Context

The study described in this paper aims to investigate how to take *parking* (P), trip *chaining* (Tc) via hubs and *new mobility concepts* (Nm) (collectively referred to as P-Tc-Nm) into account in operational travel models for densely populated regions of realistic size. The purpose of such models is to provide decision support to municipal and regional authorities.

Aggregate models for travel demand fail to account for P-Tc-Nm in an accurate manner because microscopic interaction effects are omitted. P-Tc-Nm severely affect decisions leading to individual daily travel plans while the structure of such plans cannot be captured. This is because the aggregation takes place without detailed knowledge of travel plans.Therefore, we introduce an *activity-based model* in the tool chain.

Parking availability and cost are considered both at the *home* and *remote* side of the trips.

The share of multimodal trips consisting of multiple *non-walk* components continues to increase. Widespread use of smartphone based tools is a major facilitator. On the other hand, the feasibility of such trips depends on the supply, on information about the supply but also on individual's timing and coordination constraints. A daily schedule is constrained by agreed cooperation periods (time slots) at given locations (meetings, children drop-off, pick-up, social events, daily shopping). Aggregate models cannot easily account for such cooperation and are not sensitive to changes in the cooperation constraints while exactly these are determined by P-Tc-Nm properties.

Additionally, several research projects [1], [2] argue that hubs for mode change need to provide additional facilities [6]. The basic idea of multimodal hubs is that particular classes of activities (e.g. daily shopping, meeting) may become *embedded* in a multimodal trip.

This paper focuses on an Activity Based integrated approach to model impacts of parking,hubs and new mobility concepts.

1.2. Related work

Activity-based micro-simulation models (ABM) are more detailed and keep track of individuals considering all aspects of an individual activity-travel. This includes for each agent in the synthetic population, the number of activities to be performed and specific attributes of each activity: type, start time, duration, location and a transport mode that is used to travel between two consecutive locations. Examples are Albatross [3], CEMDAP, FEATHERS[5], SimMobility, TASHA. However, these ABMs can only predict activity-travel schedules and require an assignment model (usually dynamic) for defining routes of travel and executing the predicted schedules. Literature reported several examples of such comprehensive integration of demand and supply models e.g. SimMobility[2] for Singapore, CEMDAP-MATSim [4] for Tel-Aviv (Israel) and for Berlin (Germany) [15, 16], ABM-DTALite[12] for Washington-Baltimore region (USA), FEATHERS-MATSim[1] for Bologna (Italy), ADAPTS-DTA[11] for Chicago (USA), TASHA-MATSim[9] for Toronto (Canada), to prove the point that such integration is practical and helpful in analyzing impacts of emerging policies. There are a range of policy scenarios analyzed using above integrated models e.g. land-use change and parking facility scenarios, autonomous mobility on demand, dynamic fare pricing in public transport, improvement in public transport networks. Additionally, in some efforts these models are further integrated with emission and air dispersion models to assess the impacts of transport policies on air quality.

Development of detailed integrated models requires huge efforts, however, at the same time they provide flexibility to produce results for each agent at a very fine spatio-temporal scale. Therefore, assessments of policies and scenarios not only provide understanding of first order effects but also second and third order effects [4, 2, 9]. To this end, this paper also aims to develop a similar model for a part of The Netherlands to analyze scenarios in relation to parking infrastructure and transport hubs considering new modes for travel.

[1] https://www.mobipunt.be
[2] https://www.vlaanderen.be

1.3. Process workflow

Figure 1 shows the workflow of the integrated model presented in this paper. First a synthetic population is created using a population generator. The synthetic population is input to the activity based model FEATHERS which generates activity schedules for all people within the synthetic population. The *Access and Egress mode* model refines these schedules by adding access and egress modes to the main modes predicted by FEATHERS. The resulting schedules are aggregated to OD-matrices for each mode and assigned to a network using assignment models for the main mode categories. FEATHERS and the Access and Egress mode model also use *Level-Of-Service* (LOS) matrices and land use data as an input. The LOS-matrices are generated by a classical four-step traffic and transport model for the Metropolitan Region Rotterdam - the Hague (V-MRDH) that is used in the case study of this paper. The advantage of using the LOS-matrices generated by the V-MRDH model instead of the LOS-matrices generated by the assignment models of our integrated modelling approach is that it avoids the need to estimate/calibrate the OD-matrices based on traffic counts and to apply a growth factor method, because the V-MRDH model has been extensively calibrated and validated. The LOS-matrices are the end result of an iterative process where there is an equilibrium between demand and supply and the assignment results match the traffic counts. Of course, a more advanced model set-up where the LOS-matrices generated by the assignment models are used as in an input to FEATHERS and the Access and Egress mode model (dotted arrows) could be used as well, but is outside the scope of this paper.

Section 2 describes the four sub-models of the integrated modelling approach and explains how parking, hubs and new mobility concepts are modelled in each of the sub-models. Section 3 describes the case study results for a base year including the input data, model results and validation results. Section 4 describes the conclusions and recommendations for future research.

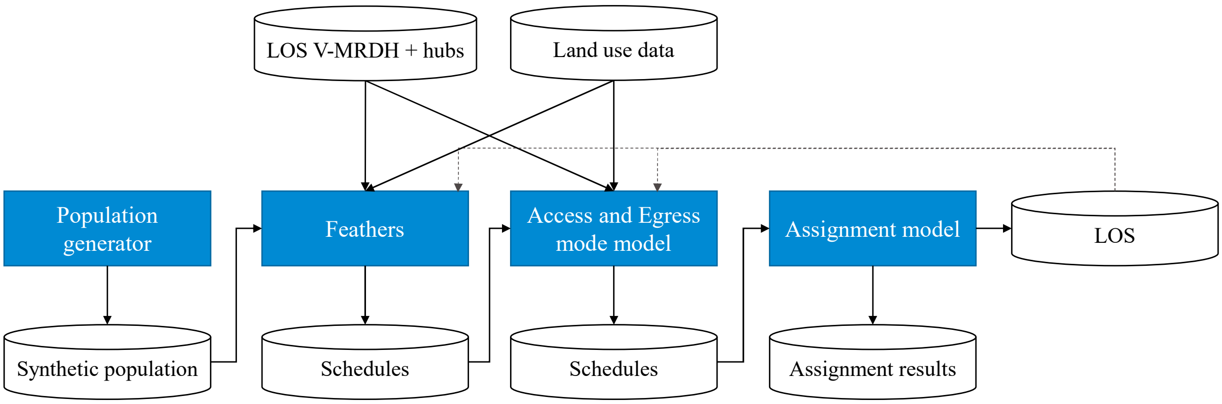

Fig. 1. Integrated modelling tools

2. Integrated activity-based travel demand and assignment model

2.1. Details about population generation

We use the well-known method of Iterative Proportional Fitting (IPF) (e.g. [8]) to generate a population. The population contains the following characteristics: person id, zone id, household id, gender, roots, age class, household composition, number of children, household income, payed work, education, student, life style, driving license, car availability, fuel type of cars, and bike ownership (no bike, normal bike, e-bike)

Since this paper contains a case study for the Netherlands, microdata from Statistics Netherlands (CBS), a Dutch national travel survey OViN, data from the national vehicle registrations (RDW) and data of the V-MRDH model are used as input. The microdata from CBS contains personal characteristics of individuals. Because of privacy regulations this data cannot be used on an individual level. The data has been aggregated to the zonal level of the model in the secured environment of CBS, exported and disaggregated again outside the CBS environment using IPF in combination with aggregated cross tables on a regional and national level.

To determine car ownership in future years when for instance new parking policies reduce the number of available parking places, a regression model has been estimated to determine the relationship between car ownership, personal characteristics like age, gender etc. and the number of parking places. To model the impact of hubs, no additions to the synthetic population were needed. To model the impact of new mobility concepts attributes have been added to the population that indicate whether or not somebody has a subscription to shared micro15km/h, shared micro25km/h and/or shared cars. Mode category definitions are found in Table 1. These attributes constitute scenario input.

2.2. *Details about the activity-based travel demand generator (FEATHERS)*

2.2.1. *Principle of operation*

FEATHERS starts from a synthetic population and predicts a schedule (daily travel plan) for each individual. A *schedule* is a sequence of *episodes* that together exactly cover the simulated period (a single day). Each episode consists of exactly one *trip* followed by an *activity*. The main predicted attributes are: (i) activity type, start time, location and duration and (ii) the main travel mode for the trip. The main loop executed for each individual is detailed in Algorithm 1. Sampling is from discrete choice models (see Section 2.2.2).

Algorithm 1 FEATHERS main loop to predict the daily activity plan for an individual

```
function DETERMINEPISODE(epi,context)    ▷ 'epi': identifies episode, 'context': environment and partial schedule
    actType ← ...    ▷ If yet unknown, sample activity type from context dependent choice model
    actLoc ← ...    ▷ Activity location from context dependent choice model
    tripMode ← ...    ▷ Travel mode from context dependent choice model
    actDur ← ...    ▷ Activity Duration from context dependent choice model
    return (actType, actLoc, tripMode, actDur)
context ← ∅
DAP ← ... ▷ Sample Daily Activity Pattern (this is a sequence of tours. Type of each primary activity is known.)
context.add(DAP)
for all epiType ∈ {HOME, WORK, SCHOOL, OTHER} do
    for all tour ∈ DAP do
        if tour.primActType() = epiType then
            primAct ← DETERMINEPISODE(context)
            context.add(primAct)
            for all st ∈ {primAct.firstTourPart(), primAct.secondTourPart()} do
                PAT2 ← ...    ▷ Sample pattern for partial tour: Sequence of episode templates (no details known)
                for all epi ∈ PAT2 do
                    secAct ← DETERMINEPISODE(epi, context)    ▷ Fill in the details
                    context.add(secAct)
```

The spatial resolution for activity locations is at *travel analysis zone* (TAZ) level. The temporal resolution is one minute. The predicted schedule is the result of a sequence of decisions as explained by Algorithm 1. Individuals are considered to be independent. The outcome of each decision is sampled from the associated discrete choice model (explained in Section 2.2.2). The result of a decision can be used as an input for a successor decision. Due to the sampling, inconsistent schedules can be generated. These are rejected and a new schedule is generated for the individual. The number of predicted schedules exceeds the population size by less than 5%.

2.2.2. *Estimation of Discrete choice models*

Observed schedules collected by OViN are used for choice model estimation by Biogeme. There are in total 28 sub-models estimated in an hierarchical manner by following an approach similar to other discrete choice model based ABMs [7, 2]. The *DAP* model at the top generates the number of tours an individual performs in a day for each type of activity. The model contains 50 alternatives in total and has a coverage of around 96% of the observed data. All models

Table 1. Mode categories used to integrate new options.

Name	Speed [km/h]	Weight	Space [pcu]	Passenger capacity	Example
Micro5	< 5	$< car$	≤ 0.25	< 1	walk
Micro15	$\in [5, 20)$	$< car$	$\in [0.25, 0.50)$	< 1	bike
Micro25	$\in [20, 30)$	$< car$	$\in [0.25, 0.50)$	< 1	e-bike
Private vehicle: drive alone	> 30	$\geq car$	> 0.50	$\in [1, 8]$	car
Private vehicle: passenger	> 30	$\geq car$	$\in [0.25, 0.50)$	$\in [1, 8]$	car passenger, taxi
Shared ride on demand	> 30	$\geq car$	≤ 0.25	$\in [1, 8]$	demand responsive transit
Shared ride traditional	> 30	$\geq car$	≤ 0.25	> 8	public transport

except the location models can be trained in an efficient way. The models for location choice are huge due to (i) the large number of TAZ, (ii) the large number of attributes for each TAZ and (iii) the large number of level-of-service (LOS) quantities involved. The number of lookups in the LOS matrices required to compute logsums was too large to be executed in the available time frame. Hence, for each OD-pair, the travel time and travel cost (weighted over the time periods of the day) of *private vehicle* and *shared ride traditional* modes are used in location choice models as a proxy to represent accessibility instead of logsums from transport mode choice model. Apart from other attributes, parking infrastructure availability (free and paid) and parking tariffs which are averaged over TAZ are included in the models where they have been found significant and with the right signs.

To model new mobility concepts we introduce a categorization of 7 main mode categories in the mode choice models for primary and secondary activities in the tour. The mode categories differ in speed $\{\leq 5, [5, 20), [20, 30), > 30\} km/h$, weight $\{< car, \geq car\}$, vehicle space per person in passenger car equivalents (pcu) $\{\leq 0.25, [0.25, 0.5], \geq 0.5\}$ and passenger capacities $\{< 1, [1, 8], > 8\}$. As a result, there are $4 \cdot 2 \cdot 3 \cdot 3 = 72$ combinations of which 65 combinations are infeasible. Most of the traditional travel modes as well as new mobility modes fit into these 7 remaining categories. An advantage of using mode categories instead of single modes is that new modes can easily be added to the model as long as they fit within one of the seven categories. The 7 categories with their characteristics are listed in Table 1.

Predictions about new modes are based on the following assumptions: (i) the preference for mode categories derived from the observed data continue to apply when new modes are added to categories and (ii) whenever a shared mode is available to a traveller, it will be chosen. The categories *Micro15*, *micro25*, *private vehicle: drive alone* and *private vehicle: passenger* are split into two categories *shared* and *non-shared* to model the concept of vehicle sharing.

2.2.3. Tool properties

FEATHERS consists of a generic part and a project specific library of choice models. Algorithm 1 belongs to the generic part. Sampling actions in lines 2 to 5 may involve multiple MNL models.

Parts involving heavy computations are written in C. Parts related to model training are written in python3 because integration in Biogeme is required. Specifications for utility functions do appear in both. Therefore, a code generator has been developed so that the models are specified exactly once and both C and python3 code are generated from a single source to guarantee consistency. Model coefficients delivered by Biogeme are integrated automatically.

The schedule prediction problem is *embarrassingly parallel*. The number of concurrent instances is limited by the huge memory requirement. Runs were executed by 6 processes in parallel. A prediction for $3.6M$ individuals completes in slightly less than 10.25 hours (i.e. predicting 100 schedules per second).

2.3. Details about access and egress mode model

The Access and Egress mode model takes the schedules that are generated by FEATHERS as input and refines these schedules by adding access and egress modes. For instance, even if a car is used as a main mode, one always has to walk to the car and walk from a parking space to a destination. In total there are 7 x 7 x 7 = 343 multimodal mode combinations of which we selected 32 feasible combinations. The main modes micro5, micro15 or micro25 always have micro5 as access and egress mode resulting in 1 multimodal combination per main mode. The main modes *private vehicle: drive alone* and *Private vehicle: drive alone* always have micro5 as access or egress mode. If mirco5 is used as access mode, micro5, micro15, micro25, *shared ride on demand* and *shared ride traditional* can be used as egress mode and the other way around resulting in 9 multimodal combinations per main mode. The main mode *shared ride on demand* always has micro5 as access or egress mode and can use micro5, micro15, micro25 and *shared ride traditional* at the other trip end resulting in 7 multimodal combinations. Finally, the main mode *shared traditional* can use micro5 and micro15 as access or egress mode resulting in 4 multimodal combinations.

The mode switches take place at hubs. A hub is a place where travelers change their travel mode within a trip, i.e., travelers use a mode to travel from an origin to a hub and then switch to another travel mode to continue their journey. Besides the 'normal' public transport stations, 48 hubs are included in the model for the case study area that can be 'switched on' or 'switched off' depending on the scenario. The 48 locations match the current park and ride locations, but other locations could be added as well. The availability of shared vehicles for each hub is also scenario input.

The utility for each multimodal mode combination is computed based on the utility functions and parameters from FEATHERS. That is the utility of a multimodal mode combination consists of a mode specific constant of the main mode and socio-demographic attributes like age, gender, driving license, car availability, household income, household composition, education level and activity type. The utilities for the parking search time, travel time, operational cost, start-up cost, parking cost are summed over the access, main and egress mode using the parameters for time and costs that have been estimated in FEATHERS for the access, main and egress modes. For combination with *shared ride traditional* as mode, a slightly different approach has been used, because the LOS for these combinations could only be generated for the entire multimodal trip at once instead of separately for the access, main and egress mode. For this reason, the total trip times and cost are used and they are multiplied with the time and cost parameter of *shared ride traditional*. The travel time and travel cost differ for private and shared vehicles. For the main modes Micro15, Micro25, *private vehicle: drive alone* and *private vehicle: passenger* it is assumed that a person uses the shared alternative when he/she has subscription of shared services even if he/she also owns a private vehicle. Furthermore, a multimodal mode combination will consist of two transfers, from access mode to main mode and from main mode to egress mode. Hence, the utility contribution of the hub transfer time is summed over these two transfers. When a private mode (e.g. car) is chosen as main mode the transfer time is assumed to be 5 minutes per transfer and when *shared ride traditional* is used as main mode the transfer time is assumed to be 8 minutes. In addition, two normally distributed error terms with zero mean and appropriately chosen variance are included. The first term is specific to the mode and traveler. It models the personal preference with respect to a mode, and is not resampled whenever the same mode/traveler combination is regarded for a different trip (both within a tour or across multiple tours), so as to enforce consistency. The second term is not only specific to the mode and traveler, but also to the actual trip. This term models any other random effects, and is resampled also when the same mode/traveler combination is considered for a different trip.

After the utilities for each trip have been calculated a set of feasible multimodal mode combinations for each trip in a tour is generated for each person. In this step constraints with respect to vehicle ownership, mode availability in the tour, mode availability at origin and destination and locations where vehicles should be returned are considered as explained in more detail in [14]. When a person has a subscription for one or more shared services some constraints are relaxed. Eventually, the multimodal mode chain having the highest utility will be selected.

A more elaborate description of the access and egress mode model can be found in [13].

2.4. Details about assignment models

The generated schedules resulting from the access and egress mode model are assigned to the network to simulate route choices made and resulting traffic delays. We use a static macroscopic traffic assignment model, and therefore the individual activity schedules need to be aggregated to Origin-Destination matrices, for each time period, for each of the mode categories. Additionally, multimodal trips are split into separate trips, e.g. a trip from origin to destination via a hub is split into one trip from origin to hub, and one trip from hub to destination.

Before assigning the OD-matrices to the network, the network and basic assignment methods are adjusted to incorporate the P-Tc-Nm. First, special parking links are added to connect the zones, as shown in Figure 2, based on [10]. The parking links have a capacity equal to the parking capacity in that zone, and also incorporate increasing parking search time. Walking links between the zone and the parking link are added as well as walking links between the zones, to represent both walking from the parking spot to the destination and walking to a zone further away if the available parking capacity is too small to accommodate all traffic. In this paper, there are several types of parking capacity considered, including parking at private terrain, free parking and paid parking. For each of the parking types a parking link is added to the network. In the assignment phase, the different purposes of the trips (work, home, business, etc.) define which parking capacity can be used.

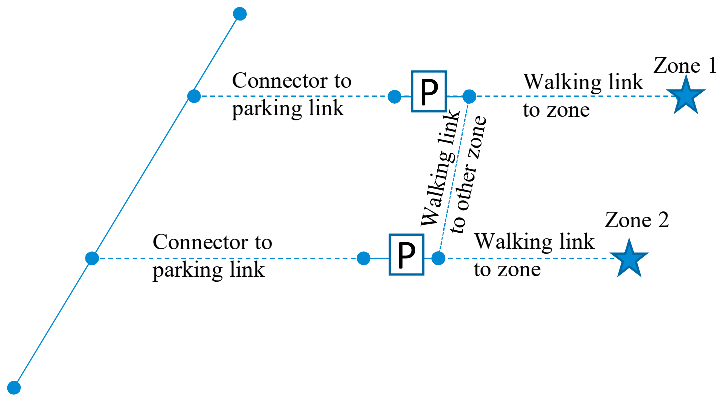

Fig. 2. Parking and walking links to model parking capacity and searching time in traffic assignment

Trip chaining is incorporated by computing the optimal hub for each trip chain of modalities, that is, a hub for a micro15-private vehicle trip, a hub for a private vehicle-micro25 trip, etc. The hubs are selected based on the minimal total travel time for both parts of the trip. Additionally, constraints are set on the maximum distance traveled, such as a maximum micro15 distance of 4 km and a maximum micro25 distance of 7 km. The computed hubs are incorporated in the access and egress mode model.

The new modalities are assigned to the network using existing traffic assignment algorithms with minor adjustments. The micro5 OD-matrix is not assigned to the network since it is not assumed to be of importance. The micro15 and micro25 matrices are assigned to the bicycle network using three All-Or-Nothing assignments where one third of the travelers chooses the path with the shortest travel time, one third the path with the shortest distances and one third chooses the path in which both the travel time and distance are minimized.The *private vehicles* and *shared on demand* modes are assigned to the car network in a multi-user class Volume Averaging assignment where different user classes are used to account for the different types of parking capacity. Using a private vehicle as passenger is not assigned to the network - it is assumed that those vehicles are already assigned to the network as a driver. The *shared ride traditional* mode trips are assigned using a public transport assignment.

3. Case Metropolitan Region Rotterdam - The Hague

3.1. Data

The considered area (The Netherlands) was subdivided into 7011 TAZ using fine granularity for the study area and a coarse one for the influence area. As a consequence, each LOS matrix consists of approx 50M cells. LOS is specified for 3 periods (morning peak, evening peak, remainder of the day) 11 travel modes (7 existing, 4 new ones) and 3 LOS quantities (distance, duration, cost) resulting in 99 matrices. LOS values are kept as a `short int` to save memory. The set of matrices uses 11.2 GB of core memory. Internal units (*hm, 0.1 min, 0.1 €*) are chosen so that the available numerical range is optimally used.

The land use dataset specifies TAZ the size of the zone, the level of urbanization, the number of inhabitants, the number of jobs per sector, the number of education places, the number of bars and restaurants, the number of stores, the number of private terrain, free and paid parking spaces and the average parking rate.

Observed one-day travel plans were taken from the OViN recurrent household travel survey in the Netherlands. Interactive GIS-based improvement was applied: PC4 based locations have been mapped to MRDH zones taking into account the relative geometrical overlap and the travel purpose specific attraction (e.g. size of schools). Each observed travel mode was mapped to one of the 7 *mode categories*.

Travel demand was predicted by FEATHERS predictions for 3.6M individuals living in the Metropolitan Region Rotterdam-The Hague.

3.2. Results

Distributions for trip length, activity duration, mode shares etc closely reflect the corresponding distributions for the observed data for the base year. The traffic flows predicted by the activity-based model approximate reality better than the standard aggregated V-MRDH model before calibration of the models (synthetic model results).

To assess the quality of the model and base year predictions, elasticity values are computed and compared with the values recommended in the Dutch national model (GroeiModel). These values are produced by 10% increasing the travel times and cost for private vehicle and *share ride traditional* separately and then running the FEATHERS simulations. Direct elasticity values computed for *person km travel* for private vehicle and *shared ride traditional* modes and are reported in Table 2. The values obtained are within the recommended ranges. Activity type specific elasticities were also computed for person km travel and they were also found in line with the recommended ranges. Further assessment of the base year model results was made by comparing average number of car-based trips (private vehicle: driver and passenger) per person generated in the morning peak, evening peak and rest of the day within study area. The values obtained from FEATHERS schedules for the 3 time periods are 0.197, 0.183 and 0.963. Similar, values are obtained from V-MRDH model and the values are 0.156, 0.202 and 0.974. Comparison of these values indicate that they are consistent with V-MRDH.

Table 2. Results for transport modes direct elasticities

Transport Mode	Obtained values		Recommended values	
	(Travel time)	(Travel cost)	(Travel time)	(Travel cost)
Private Vehicle: Driver	-0.51	-0.40	-0.30 to -0.70	-0.20 to -0.50
Shared ride traditional	-0.75	-0.59	-0.6 to -1.3 (Bus/tram/metro) -0.5 to -0.7 (train)	-0.60 to -1.20

3.2.1. Results Access and Egress mode model

For the base year only multimodal combinations with *shared ride traditional* have been considered. The results are shown in Table 3. The three columns on the left contain the results from the access and egress mode model and the three columns on the right contain the results from the V-MRDH model. The results show that the modal split of the Access and Egress mode model matches the modalsplit of the V-MRDH model quite good. A comparison with travel survey data from OViN cannot be made because bike (mirco15) as access and/or egress mode is known to be underrepresented in this survey.

Table 3. Results Access and Egress mode model.

	Access and Egress model			V-MRDH model		
	Morning peak	Off peak	Evening peak	Morning peak	Off peak	Evening peak
micro5 Shared ride traditional micro5	54%	53%	57%	51%	42%	58%
micro5 Shared ride traditional micro15	12%	22%	34%	7%	23%	26%
micro15 Shared ride traditional micro5	30%	23%	5%	35%	31%	9%
micro15 Shared ride traditional micro15	4%	2%	5%	7%	4%	6%

3.2.2. Results traffic assignment

The generated schedules have been assigned to the V-MRDH 2.6 networks of car, bicycle and public transport. The trip lengths of the synthetic ABM assignment and the V-MRDH calibrated outputs are shown in Figure 3. It can be seen that the trip length distributions are in general quite similar. However, for the short distance trips the ABM overestimates car and public transport trips and underestimates bike trips compared to the calibrated V-MRDH results. Additionally, a comparison has been made between the vehicle delay hours and vehicle kms driven between each of

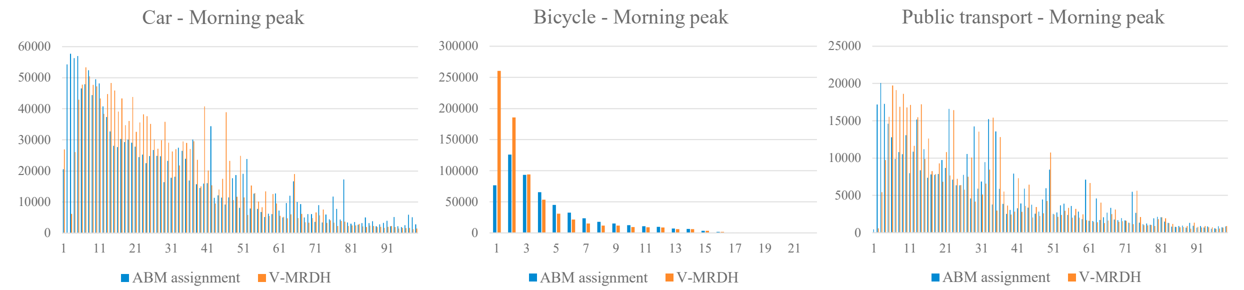

Fig. 3. Trip lengths distribution in km for car, bicycle and public transport compared to calibrated V-MRDH-results, for the morning peak time period

the two simulations. Results are shown in Table 4. In general numbers correspond, which indicates that the ABM is producing output in line with the observed schedules. It is interesting to note that in the ABM the computed delay is a bit lower than in the V-MRDH model whereas the vehicle kilometers driven are more or less equal or higher. This can be improved in a calibration step. To simulate limited parking capacity and according search and/or additional walking

Table 4. Results traffic assignment

	ABM assignment model		V-MRDH model	
	Morning peak	Evening peak	Morning peak	Evening peak
Vehicle delay hours	54070 h	48161 h	57305 h	64450 h
Vehicle kms driven	66.9 million	66.2 million	64.0 million	66.0 million

time, parking links were introduced in the traffic assignment. This leads to 25% of the cars parked in a different zone then their destination due to a shortage of parking capacity in the morning peak, as is shown in Table 5. In only 20 to 25 of the zones the capacity of parking lots has been exceeded, showing that the introduction of parking links indeed works. By running additional iterations of the model chain, this number can be further decreased.

Table 5. Results parking link usage in traffic assignment

	Usage of paid parking	Cars parked in a different zone	Capacity exceeded	Average occupancy parking lot
Morning peak	99079	25%	20 (of 7786 zones)	6%
Evening peak	149953	9%	25 (of 7786 zones)	9%

4. Conclusion and future work

The new integrated activity based approach proved to be better suited to model impacts of parking, hubs and new mobility concepts than the standard aggregated modelling approach, because: (i) The *microsimulation* activity based approach can consider mode availability and interaction effects on an individual level, which allows for detailed MaaS scenario experiments. (ii) The Access and Egress mode model can model mode switches of individuals at hubs and can consider constraints with respect to vehicle ownership, mode availability in the tour, locations where vehicles should be returned and mode availability. (iii) The inclusion of hubs and parking links in the assignment model makes it possible to generate LOS-matrices that include travel time and cost for travelling via hubs and parking search and walking time. These LOS-matrices are input to the activity based model and Access and Egress mode model.

The results generated by the synthetic model for the base year look promising because they closely resemble observed schedules and the elasticities are within the recommended ranges mentioned in literature. Moreover, a comparison with the calibrated results of the V-MRDH model shows a reasonable fit, which can be further improved by calibration of the model.

The research presented in this paper is part of an ongoing project called Urban Tools Next II in which also model runs will be done for: (i) a reference case in 2030, (ii) a 2030 situation with reduced private and public parking spaces and (iii) a 2030 case where 50% of the people use shared modes. These model runs might result in new insights that can be used to further improve the model and base year results.

The next step will include methodological improvements to model parking (with focus on parking cost which is a property of an activity sequence and not of a trip). Finally, effects of Covid on travel behaviour (tele-work, avoidance of PT) need attention.

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