D5.3 Implementation of the MOMENTUM Decision Support Toolset in Madrid, Thessaloniki, Leuven and Regensburg

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Summary sheet

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Abstract	In this deliverable the procedure is described of the calibration and validation for all Levels of the Decision Support Toolset. It includes all cases studies of the cities participating in the MOMENTUM project along with the actions followed in order to coordinate each case study. The presented methodologies are based on findings deriving from previous deliverables and WPs, summarizing methodologies and procedures followed in the four cities participating in the MOMENTUM project: Thessaloniki, Madrid, Regensburg and Leuven. The implementation in the city of

	Thessaloniki will work as a test bed for the implementation in the rest of the cities. The developed toolset will tackle the needs of policy and decision makers identified in WP2 and will be based on the outputs and capabilities of the new data analysis and modelling techniques developed in WP3 and WP4 respectively.
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Project partners

Organisation	Country	Abbreviation
EMPRESA MUNICIPAL DE TRANSPORTE DE MADRID SA	Spain	EMT
NOMMON SOLUTIONS AND TECHNOLOGIES SL	Spain	NOMMON
DIMOS THESSALONIKIS	Greece	THESS
ETHNIKO KENTRO EREVNAS KAI TECHNOLOGIKIS ANAPTYXIS	Greece	CERTH
STAD LEUVEN	Belgium	LEUVEN
TRANSPORT & MOBILITY LEUVEN NV	Belgium	TML
STADT REGENSBURG	Germany	REGENSBURG
TECHNISCHE UNIVERSITAET MUENCHEN	Germany	TUM
AIMSUN SL	Spain	AIMSUN SL
POLIS – PROMOTION OF OPERATIONAL LINKS WITH INTEGRATED SERVICES, ASOCIATION INTERNATIONALE	Belgium	POLIS
UNION INTERNATIONALE DES TRANSPORTS PUBLICS	Belgium	UITP
UNIVERSIDAD DE LA IGLESIA CATÓLICA DE DESUTO ENTIDAD RELIGIOSA	Spain	UDEUSTO

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Issue 1 Draft 3	22/11/2021	CERTH		

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List of acronyms

AI	Artificial Intelligence
BS	Bike sharing
BSS	Bike sharing system
CS	Car-Sharing
CSV	Comma-separated values
DRT	Demand Responsive Transport
DST	Decision Support Toolset
DSS	Decision Support Systems
EV	Electric Vehicle
FCD	Floating Car Data
GeoJSON	Geographic JSON
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
KM	Kilometre
MAE	Mean Absolute Error
OD	Origin-Destination
OR	Operational Research
PT	Public Transport
RS	Ride Sharing
RMSE	Root Mean Square Error
SHP	ShapeFile

SUMP	Sustainable Urban Mobility Plan
SS	Scooter Sharing
TAZ	Traffic Analysis Zone
WP	Work Package

1 Introduction

1.1 Scope and objectives

The overall goal of the MOMENTUM project is to develop a set of mobility data analysis and exploitation methods, enhanced transport models and advanced decision support tools, which can capture the impact of emerging transport modes (such as shared mobility services) and ICT-driven behavioural changes on urban mobility. The developed methods aim to support local authorities in the task of designing the right policy mix, to exploit the full potential of emerging mobility solutions

Decisions on transport policy measures have long-term and important impacts on economy, environment, and society. Transport policy measures can lock up capital for decades and cause manifold external effects. In order to allow European policy-makers to evaluate transport polices, the MOMENTUM consortium envisaged a decision support tool that facilitates the evaluation of the economic, environmental and social impacts of the implementation of transport policies.

Based on the methodology described in previous WPs for each case study of the MOMENTUM project and moving towards WP6, Deliverable 5.3 “Implementation of the decision support toolset in the case study cities”, is considered as a transition procedure, describing the calibration and validation process of the four transport models and the implementation of the interactive decision support toolset in the four case studies participating in MOMETUM project, adapted to the scope and requirements of each case study. In T5.3, the enhanced simulation tools resulting from D5.1, D5.2 and the decision support dashboard developed in T5.2 is implemented in the four case study cities. The simulation models are calibrated using the supply and demand data collected or produced in WP3. As for the interactive decision support dashboard, the policies under consideration and the KPIs are tailored to the specific requirements of each city. The implementation in the city of Thessaloniki is used as a testbed for the implementation in the rest of the cities. The new toolset is implemented on top of the existing mobility ecosystem, which holds a variety of data analysis. Finally, the process of the work conducted in WP5 will be used as the project moves towards WP6, where the results of the implementations in WP5, will be presented along with the outcomes of the investigation of methodologies.

1.2 Structure of the document

The goal of this document is to present and describe all the methodological steps of calibration and validation for the four case studies. In a nutshell, this document consists of the experience gained in the three Levels of the DST for each city, the steps moving forward to WP6 as well as the discussion of the experience gained. In detail, the remainder of this report consists of the following sections:

Section 2 describes the preparation of input data for every city for Level 1, calibration of those data in order to be used by the developed DST and the validation of the input data by testing the DS toolset. Furthermore, a description of the work done is included alongside with the potential improvements and modifications implemented in Level 1.

Section 3 describes the preparation of input data for every city for Level 2, calibration of those data in order to be used by the developed DST and the validation of the input data by testing the DS toolset. Furthermore, a description of the work done is included alongside with the potential improvements and modifications that need to be done in Level 2.

Section 4 describes the preparation of input data for every city for Level 3, calibration of those data in order to be used by the developed DST and the validation of the input data by testing the DS toolset. Furthermore, a description of the work done is included alongside with the potential improvements and modifications that need to be done in Level 3.

Section 5 describes the general outcomes of the calibration and validation process of WP5 from the city partners and the link of WP5 moving towards the preparation and implementation of WP6.

In section 6, reader can find the references used for the writing of this document while on the last section are described the values used for all cases studies in calibration and validating the Decision Support Toolset developed

1.3 Applicable documents

[I] Grant Agreement No 815069 MOMENTUM – Annex 1 Description of the Action.

[II] MOMENTUM Consortium Agreement, Issue 1, April 2019.

[III] MOMENTUM D1.1 Project Plan, June 2019

[IV] MOMENTUM D1.2 Data Management Plan and Open Data Policy, November 2019

[V] MOMENTUM D2.1 “New Mobility Options and Urban Mobility: Challenges and Opportunities for Transport Planning and Modelling

[VI] MOMENTUM D2.2 Specification of MOMENTUM Test Cases, February 2020

[VII] MOMENTUM D3.1 Data Inventory and Quality Assessment, March 2020

[VIII] MOMENTUM D3.2 MOMENTUM Data Repository, June 2020

[IX] MOMENTUM D3.3 Methodologies and Algorithms for Mobility Data Analysis, December 2020

[X] MOMENTUM D4.1 Transport Modelling Approaches for Emerging Mobility Solutions, May 2021

[XI] MOMENTUM D4.2 Open Repository of Demand and Supply Models and Algorithms for Emerging Mobility Solutions

[XII] MOMENTUM D5.1 Enhancement of Transport Simulation Frameworks with Models of Emerging Mobility Solutions

[XIII] MOMENTUM D5.2 Interactive Decision Support Tool

[XIV] MOMENTUM D6.1 Policy Assessment Methodology

2 Calibration and validation of DST- Level 1

2.1 Introduction

The main objective of this level of the DST is to identify the outlines of potential interventions in the urban mobility characteristics of a city. Key elements of this step are to define city's needs, perform economic and technical analysis for emerging urban mobility in the city. Level 1 is an automated procedure and requires a small amount of input data, such as geospatial socio-economic data about the population of the studied area and the available operating fleets of mobility services.

Depending on the applicable urban mobility scheme, the appropriate analytical approach will be implemented. Due to the low granularity of input data, assumptions will be made so that decision makers can receive an initial step of potential urban mobility plans at a very low cost in terms of data. Further information about the methodology and the theoretical background followed in Level 1 of the DST can be found in the D5.2 "Interactive Decision Support Tool".

Below the described procedure will be presented for the city partners of the MOMENTUM project.

- Thessaloniki's case study will be used as a test bed for the other cities. Thus transportation data from the city were used as a test through the process of implementing the tool alongside with the municipality of the city. All services were tested in the city
- Several tests were carried out for Regensburg based on the specific operator costs. The first tests took place in May 2021, further tests in July 2021. In September 2021, the development changes made in the tool were checked. For the case of Regensburg the systems of bike sharing and ride sharing were tested
- For the case study of Madrid, tests carried out for the city, where the bike sharing system is operating in order to validate and calibrate the system. Extending the testing area, Madrid included in the tests smaller subareas of the city (Arganzuela and Salamanca)
- In the case of the city of Leuven Level 1 tests were not used for testing, as services currently operating are covering the existing demand. The critical role of the city of Leuven in this level of the DST was to calibrate and validate the tool.

Validation of the methodological procedure followed in Level 1 of the DST, was based on values cities' provided. The input data were received in order to validate Level 1 was twofold: on the one hand were associated with the values used for testing the DST while on the other hand, the expected or existing values of services (number of stations, docks per station, number of bicycles), currently operating the areas tested. Based on the validation of the values given and feedback received, the calibration of Level 1 was implemented. It is important to mention that level 1 is an optimization process, so it will not provide the real values, but the optimum based on the mathematical formulations and the hypothesis, however, based on the results expected by the cities various mechanisms to "calibrate" the way the problem is optimized were included in order to allow the cities to ask for more "social" solutions and less economic. Features added to the tool, targeted to the expansion of possibilities to the city partners, to assess the impact from user's perspective or from the operational side. Furthermore, the addition of the sensitivity analysis of demand option in Level 1, aimed to give user of the DST, the ability to receive a range of solutions, not only the optimal values of the tool, in order to define the most applicable set of interventions.

In the Annex of this document, the reader can find the values used for all case studies, in the available services of the DST. Values in the tables of the Annex include all the variables used for every case as input data, for the needed parameters. In the MOMENTUM project, the city partners have tested specific services that are of their interest. For the cities where the services were not tested, the values are not included in the tables.

2.2 Data preparation

In this section is described the data preparation procedure followed by all city partners participating in MOMENTUM project. This section includes all the actions followed in order to adjust the transportation input data of each city, in order to be compatible to the online version of the DST.

Thessaloniki

Thessaloniki's case study is focused on how a DRT service should be implemented to contribute to sustainable mobility in the city, the role of ridesharing in the transport system of the city and the impacts of bike-sharing and micromobility in transport planning. Socioeconomic and functional variables' characteristics that were used as input data for Level 1 implementation calculated as a part of the SUMP process in 2018 for the city of Thessaloniki.

The implementation of Level 1 has been done, based on the recent updated and calculated values for the city of Thessaloniki. Socio-economic and functional variables data such as the demand for services and value of time were calculated using a stated preference study, in the city of Thessaloniki for the purpose of preparing the new SUMP for the city. Values like the cost of operation were calculated based on operational costs of existing systems in the city.

On the 23rd of June, CERTH organised a workshop with local stakeholders and municipalities from other Greek cities, where the DST was presented. Feedback and comments were received, according to which improvements to the online version of the tool were made. As Thessaloniki was used as a test bed for all other cities of the MOMENTUM project, the values used for the city are the default values in the online version of the DST, so that the users can assess the calculation of the values needed for their own cases studies.

Madrid

The Level 1 of the DST tool has been tested using real data from BiciMAD, the public bike-sharing service operating in the centre of the city of Madrid. The service has nearly 3,000 bicycles with electric support that are capable of reaching 18km/h and have to be parked in one of the 290 fixed stations distributed through the city (2021). The service started operations in 2014 and from 2016 is managed by the public transport company of Madrid (EMT, Empresa Municipal de Transportes).

The estimation of the demand has been obtained using the region-wide household mobility survey of 2018 and the service operation data (October 2019 and February 2020). This information is publicly available by the city`s open data portal provided by the city council. The costs associated with the operation of the service have been derived from the financial information reports published periodically by BiciMAD. For other parameters, (such as value of time or the estimated walking distance) default values have been used.

Regensburg

The focus of the Regensburg case study is on station-based car-sharing and station-based bike-sharing systems. For car-sharing, REWAG, which is responsible for operating the "EARL" fleet, determined the relevant cost parameters based on the average values of the existing vehicle fleet. Concerning bike-sharing, the service is yet to commence operation. Therefore, the input values are created based on a recent tender document, which is meant to initiate bike-sharing service in Regensburg. Due to a lack of operator knowledge, there is a greater uncertainty with regards to cost parameters.

The input values for the socio-economic and other functional variables are trivial. Within the set of required input variables, the demand is the most vital. The actual demand is not known in Regensburg, as the supply does not yet exist, nor are they in a trial phase. An accurate estimate is required here, which will be generated later. For now, several tests with different values (100, 400, 800 trips/h) are carried out to see how the DST reacts.

Leuven

For the city of Leuven the application of level 1 services was not used for investigate new services, because the characteristics of the envisioned shared-transport systems require a higher level of granularity that is beyond the scope of level 1. These services are instead tested in level 2 and 3.

2.3 Improvements and modifications

As part of MOMENTUM project, the implementation of each of the three Levels was first evaluated in the city of Thessaloniki, which is used as testbed. After this initial analysis then, each city partner has tested the DST based on their own case study. Guidelines describing each step of the testing procedure of each level were sent to the city partners. After the testing process was completed, feedback with comments and suggestions for further improvements of the DST were proposed. It is important to be mentioned that the purpose of Level 1 is to give to the cities the ability of testing different services with less granular input data. The absence of extensive input transportation data, might lead to reduction of the level of confidence of the produce results.

Thessaloniki

The city of Thessaloniki was used as a testbed for the other city partners of the project. Thus, all services were tested and calibrated based on the values used in Thessaloniki. Based on the operational cost, socio-economic and functional variables calculated through the implementation of the city's SUMP, those values were used for the implementation of Level 1.

For the bike sharing service in Thessaloniki, different scenarios were tested. Different scenarios included changes in the operational, socio-economic variables and estimated demand for bicycle trips in the examined area. Weight assigned for the cost of the user was tested in the values between 0, 1 and 1, in order to investigate the impact of the cost of using the provided service to the users. For the tests included in the Annex, are included the tests with the weight of 0.5, as this values was calculated to be more associated with the case study of Thessaloniki. Furthermore, the maximum waiting time was tested for values ranging from 1 to 6 minutes, while the maximum walking time the users need to walk to reach a station, fluctuated from 5 to 10 minutes. Decision variables included minimum and maximum values for the number of stations and docks, were selected based on the current number of stations and units, operating in the city. In Thessaloniki, the available bike sharing system is not sufficient to cover the demand of users. Hence different scenarios were tested in order to identify the best solution. Finally, the demand range that was tested varied between 80 and 120 percent of the demand.

For the scooter sharing service, the same approach was followed as in the bicycle sharing service using the operational costs, socioeconomic variables and constrains. However, due to the fact that scooter services were included in the available transport services of the cities in 2018, no long-term data are available for this service operating in the city. Hence, different scenarios and tests were examined, based on information collected from scooter providers and surveys that CERTH conducted in order to assess the information of citizens for scooters.

In the case of the testing of DRT services in Thessaloniki, different scenarios were examined. With an average demand of 20 trips/hour, tests with different demand values were performed. The tests included the increase of demand, which consequently led to the increase of demand of DRT buses to cover the demand. Finally the constrain of the demand sensitivity module added to the DST, limited the outliers values given from the tool, without the activation of the constrain.

Madrid

The tool was tested for the current area of the service of BiciMAD in order to provide feedback, and also to validate the tool. The parameter values provided by the tool for optimal location and fleet sizes were compared with the real ones. Additional experiments with smaller sub-areas of the city have also been explored. By comparing the results of the tool with the current location and fleet sizes

In these experiments the following issues were detected, and have been solved:

- The number of stations proposed by the system were very low for the demand volume of the city.
- The upper limit for the number of stations was very low. Concisely, it was set to 90 where the system has up to 290 stations. Now the system supports any upper limit of stations.
- The way the information is displayed to the user was not intuitive
    - There existed some minor issues with a flag provided by the application where the specified constrains (such as walking distances) were not respected. Specifically, the flag "constraint not respected" appeared in total walking time estimations even when the constraint was being respected. This issue has been already resolved.
    - Finally, the estimated optimal number of docks was being displayed in a way that it was unclear whether the docks indicated were accumulative or per station. It has been now updated to "optimal number of docks per station" solving the issue.

Regensburg

In the case of car sharing, it turned out that the waiting time factor is irrelevant for Regensburg, as the vehicles are booked in advance via the app. This waiting time can ideally also be set before the booking process, so that no change in the results is expected. As such, the optimal number of stations should depend solely on the maximum walking time to the station, and not also the waiting time. With a demand of 400 journeys/hour, an optimal number of 14 stations and 7 docks was determined. That would be 400 journeys per hour with 100 vehicles. The results seemed implausible as the produced values were not meeting the expectations set and a further developed version of the DST was awaited. With the further developed version, a short manual about the functionality of the tool was made available. The next test took place in July 2021 and was presented at the Community of Practice meeting on July 13, 2021. In this revised version, in addition to the optimal number of stations and docks, the optimal number of vehicles is also determined. From this, it can be concluded that not all vehicles return to their station, but rather rotated between the stations. In Regensburg, the car sharing system is designed for errand trips; the urban area is not so large that trips between stations. The vehicles in Regensburg are booked at a station in order to undertake an errand trip (e.g., furniture store) and then the vehicle is returned at the same station. As a result, it can be stated that the car sharing offer in Regensburg is not comparable to the scope of the DST Level 1. Hence, it was decided that the tests for DST Level 1 for car sharing will be discontinued.

The tests for **bike sharing** were carried out in parallel to the tests for car sharing. After the operator costs have been derived from a tender, the first step should be to simulate the planned situation through the test. The bike-sharing system planned for Regensburg with 300 pedelecs and 300 conventional bicycles, which are to be operated as station-based, corresponds to the option “Vehicle Sharing (bike-station)” service in the DST. The first test in May 2021 was used to provide the future client of the bike sharing service, Stadtwerk Mobility, with an insight into the tool. Here, too, there was a suggestion that the waiting time for this service is irrelevant, since the vehicles should be booked via the app. This waiting time can ideally also be set before the booking process, so that no change in the results is expected. The results show a plausible picture. The operator costs increase with the increase f the number of stations and docks. The maximum walking time decreases with increase of the number of stations.

A subsequent test in July 2021, with a revised version of the DST, showed that the operator costs determined in the tool matched Regensburg’s authorities approaches, if the system is to determine the number of vehicles and stations.

3 Calibration and validation of DST -Level 2

3.1 Introduction

The aim of this level is to analyse and evaluate the design of emerging mobility systems using data driven methods for input data. In line with the analysis of the initial level of the DST, Level 2 is an automated procedure that can be performed online. The nature and the level of analysis of input data in this Level, is more comprehensive and user need to perform data preparation to import transportation data on the applicable format.

The added value of the Level 2 is based on the level of analysis that can be achieved. Granularity of input data lead to the development of an in-depth analysis of the proposed modes of transport. For the estimation of the supply of the existing demand distribution, different algorithms are implemented in order to conclude to efficient mobility service options. Through the procedure's steps of Level 2, various transportation data sources can be used in order to provide the most accurate calculations. Information on the bicycle network, public transport stops and the road network, will produce more accurate results.

Level 2 provides data driven information for the services tested, providing comprehensive operational and planning results. More information about the methodological approach followed in the Level 2 of the DST are described in the D5.2 Validation of the methodological procedure followed in Level 2 of the DST, was based on values cities' provided. The input data were received in order to validate values used for testing the DST with expected or existing values of services currently operating in the areas tested. Based on the validation and the feedback received, features and methodologies of visualizing and presenting results, were added to the tool. Finally, available transportation information city partners provided, from data driven information to OD matrices, scripts were produced and provided from CERTH, in order to produce the appropriate format of input data for Level 2 for all study cases.

3.2 Data preparation

Level 2 aims to embody methods that utilize the spatially distributed data from trips or ODs to perform strategic decisions for the service. The user of the tool should define the desired characteristics of the service to let the algorithm decide the resources needed to fulfil the requirements. In that step the user should tune values of demand in the examined area, road network and constrains such as bicycle network and public transport stops. Based on those criteria the planning module can return the optimal number and location of stops/docks, the capacity of vehicles or stops and similar system parameters. The operational module helps to evaluate each strategic setup based on performance metrics. Those metrics also used in the optimization of planning parameters as they reveal possible surpluses or shortage of resources for the service. In this section, is described the calibration and validation method followed in the case studies of MOMENTUM project.

Thessaloniki

The dataset used as input for Level 2 for the case study of Thessaloniki consists of taxi trips that are operating in the city. This dataset records are produced after processing the spatiotemporal taxi vehicle records, by on-board receivers of GPS devices. All information for each realized trip from 2016 onwards is recorded, including the coordinates and timestamp of the trip start and end, the temporal duration and travelled distance. The raw taxi data are anonymized and published by the Hellenic Institute of Transport, CERTH. The taxi fleet that generates the raw dataset operates under the name "Taxiway" taxi association, which consists of around 1000 taxis (around half of the taxis in Thessaloniki). These data are used as an approximation of the demand for both DRT and vehicle sharing services. Even if the actual demand could not be estimated directly, the methodology uses information from the taxi demand trips, makes use of the data to estimate the flow of mobility patterns into the study area.

Thessaloniki leverage the trip data option of the DST. In fact, for the Thessaloniki use case the demand input data are trips generated from taxi trajectories. This database, is transformed in the proper format as presented in Figure 1. Each trip has origin-destination coordinates and a timestamp. The dataset is manipulated in the proper JSON format according to the DST guidelines.


```
"0": {
  "time_end": 17,
  "time_start": 17,
  "trip_distance_meters": 2.3234289271935604,
  "trip_duration_seconds": 4.646857854387121,
  "trip_end_geog_Lat": 40.63317499409917,
  "trip_end_geog_Long": 22.94539655916766,
  "trip_start_geog_Lat": 40.63215270332661,
  "trip_start_geog_Long": 22.972896981713386
},
```


Figure 1: Trip data format.

This use case also uses the bike-lane network (see Figure 2) across the city centre and the bus stops (see Figure 3 of PuT network in the region of Thessaloniki. The networks were transformed from the SHP format to a GeoJson file in Python with the use of libraries such as JSON, geopandas, and shapely. The aim of those files is to locate the stations of vehicle-sharing system close to bike-lanes, as well as, to integrate the DRT service with pre-existing PuT network.

Figure 2: Bike-lanes network of Thessaloniki

Figure 3: Public Bus Network of Thessaloniki

There are 2 scenarios that are evaluated in the case study of Thessaloniki. The first scenario, regards sharing systems (scooter sharing) in the area of Municipality of Thessaloniki. The second regards a DRT service in the regions of Thermi, Pylaia, and Panorama that are more suitable for the deployment of the DRT service. The taxi trajectories are extracted from the CERTH/HIT database and analyzed with Python to get the proper structure. The taxi trips with costumers were only used for the scope of the experiments. Based on each scenario, the data is filtered only for the study areas. Thus, for the bike-sharing services only the trips that fall in area of Figure 4 extracted. Similarly, for the DRT service the points inside the Figure 5 are extracted. More precisely, each trip used for each case should have both origin and destination coordinates inside the study area.

Figure 4: DRT service area

Figure 5: Vehicle - Sharing service area

The benefit of using spatially distributed data (see Figure 6) is that it allows to locate the service station as close as possible to the origins of the demand trips. The dataset contains demand for every hour of the day for one month of 2019. However, during the final implementation a larger dataset can be used to extract more reliable results. For the use cases that trip data are not available CERTH/HIT supported the transformation of the data in the proper format.

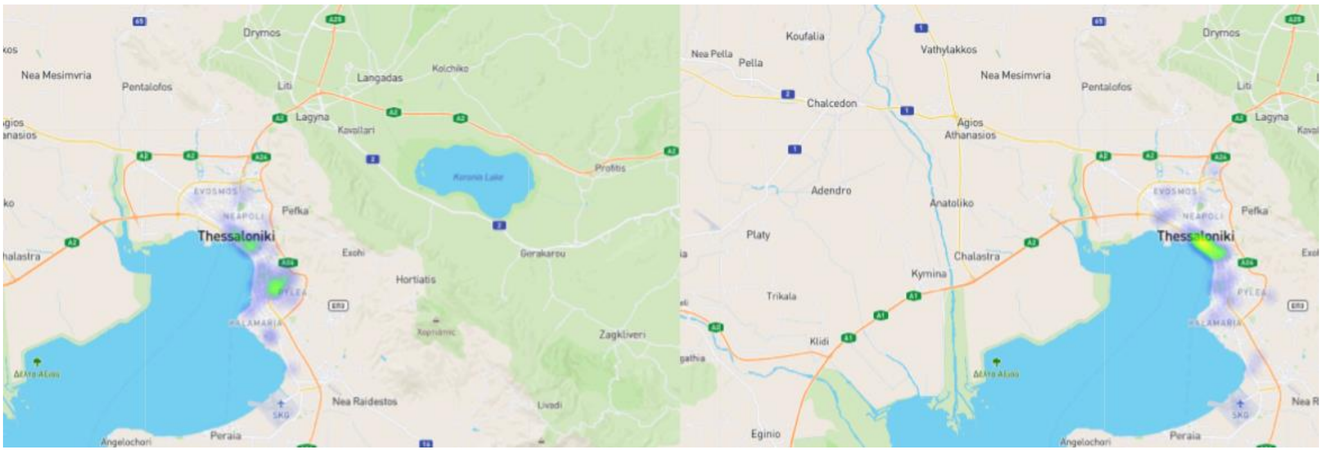


Figure 6: Illustration of Spatial distribution of origin and destination of the trips.

The second step of level 2 generates a set of candidate locations for the service stations. Those stations distributed according to the spatial distribution of the demand. Thus, more dense areas have larger number of station candidates. The third step of the tool is to extract the set of final stations of the service. Those stations could be extracted also in a JSON format. The Figure 7a and Figure 7b depict an example of the final location of stops/stations for scooter sharing and DRT services respectively.

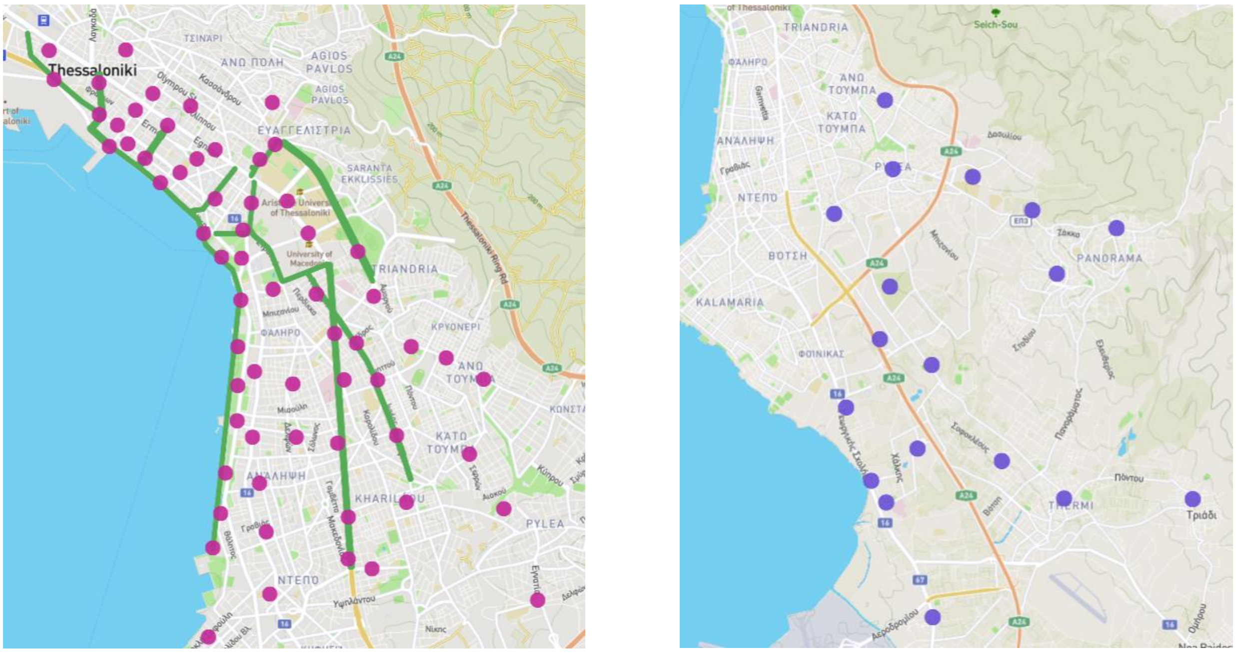


Figure 7: a) Scooter sharing stations *b) DRT stations*

The last section of the level-2 illustrates some critical service level related KPIs and strategic parameters. Those parameters help the user to understand the impact of their design in the overall system performance (Figure 8).

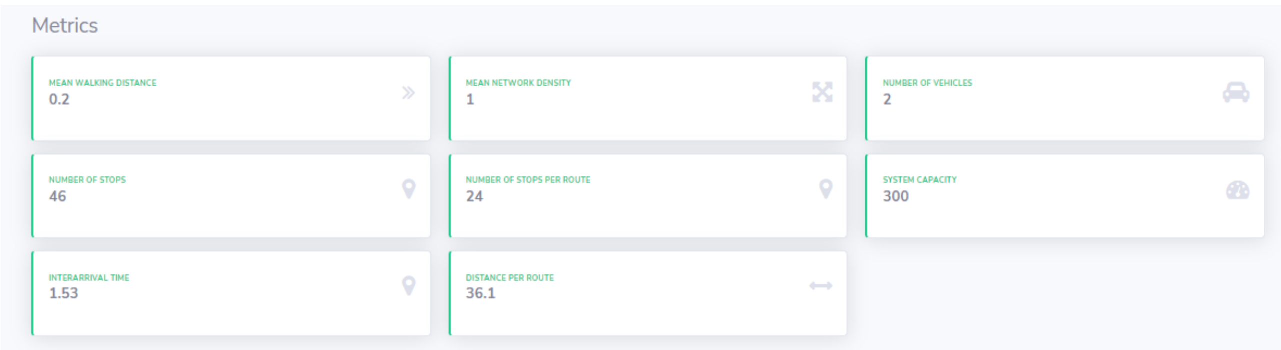


Figure 8: Example of KPIs for a given system

The last section of the level-2 illustrates some critical service level related KPIs and strategic parameters. Those parameters help the user to understand the impact of their design in the overall system performance.

<u>Madrid</u>

For the case of Madrid level 2 testing, the BiciMAD service has also been used. The specific inputs have been prepared as detailed below:

- The geographical area to be simulated has been defined in a GeoJSON file and uploaded to the service as Polygons file. The geographic information of the defined areas has been downloaded from the Madrid regional transport authority (CRTM) and is shown in Figure 9.

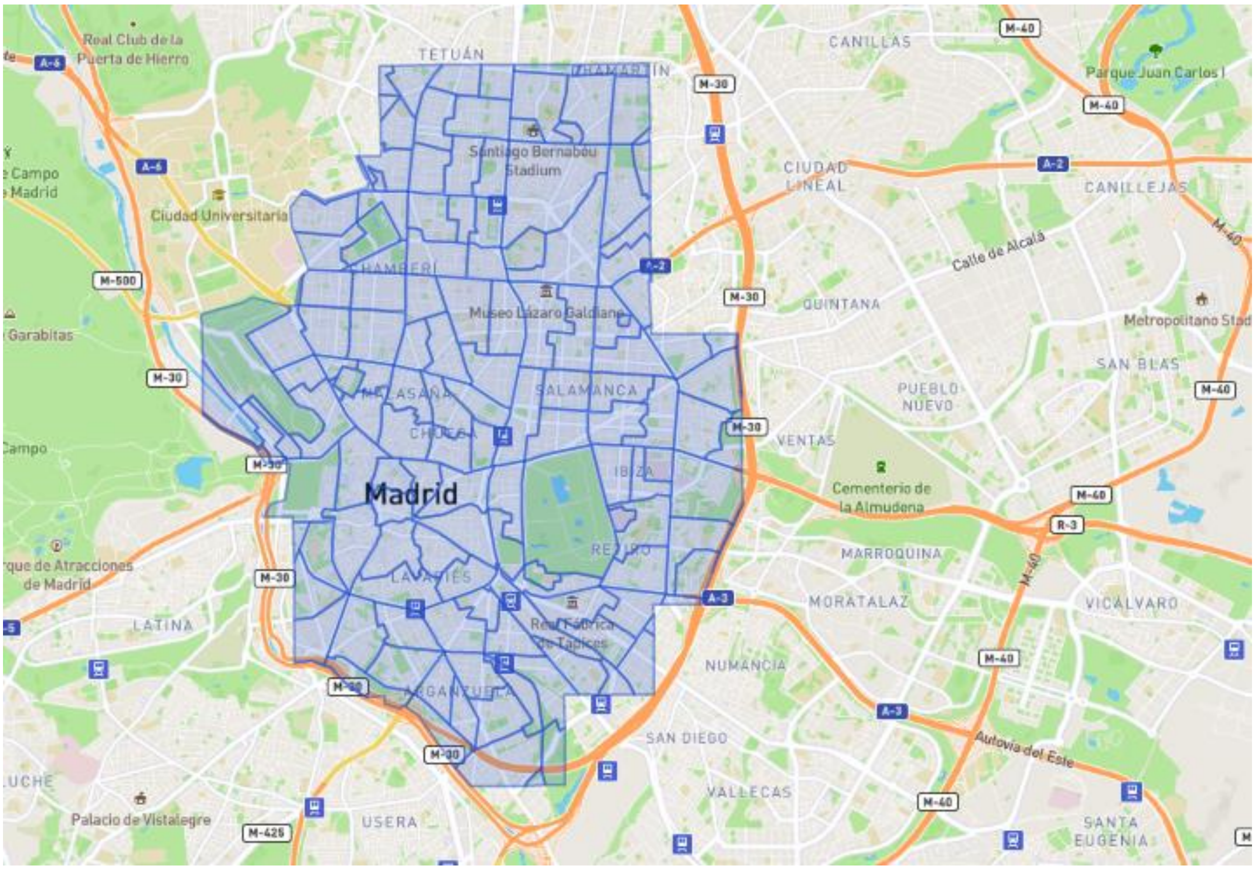


Figure 9: Area covered in Madrid

- Shared mobility matrices have been generated in order to capture the expected demand of the BiciMAD service in the city. These matrices have been obtained by counting all the trips per OD pair observed in the public open dataset for BiciMAD services in the months of October 2019 and February 2020. All trips have been associated to the geographical area file that is passed along with the demand information. Demand is computed by aggregating all the trips registered per OD pair for a given day. This data has been transformed following the DST guidelines as shown in Figure 10

```
{
    "odMatrix":{
        "0":{
            "hour":0,
            "od":{
                "1":{
                    "1":0,
                    "27":0,
                    "5":2,
                    "3":0,
                    "6":0,
                    "20":0,
                    "12":0,
                    "24":0,
                    "13":0,
```


Figure 10: OD matrix data format

<u>Regensburg</u>

The usage of level 2 requires disaggregate data. For the Regensburg case study, these data have been generated based on the aggregate OD matrices from the available travel demand model for the city of Regensburg in the VISUM software. The model uses a specialized demand generation method from PTV, which is a tour-based approach and is called VISEM. In the following paragraphs, the process of extracting the OD matrices, using the Component Object Model (COM) interface of PTV VISUM, is described. The OD matrices in the Regensburg model are defined in a 24-hour time frame. This shortcoming is mainly due to the calibration pprocedure, which adds 24-hour matrix corrections (i.e., a single static demand for a 24 hour time horizon). As a consequence, a segmented approach is taken to extract the hourly demand of the network. The segmented approach is based on providing the VISEM generated demand in an hourly time intervals, meanwhile presenting the calibration and external demand matrices as 24 hour demand.

Even though the Regensburg model is intended to create 24 hour matrices for the OD demand, the VISEM platform allows the creation of output matrices in a different format, with some options being segmented by person group, mode and more importantly time frame. The format of VISEM generated OD matrices, in the case of Regensburg, differs between demand segments. For instance, demand segments such as walking, bicycle and private car, the 24-hour matrix are estimated in only one instance of the model. Conversely, the public transport OD matrix is estimated in three time intervals, which correspond to 6:00-8:30; 16:30-19:00; and 8:30-16:30. However, the latter interval (i.e., 8:30-16:30) is a result of the subtraction of the 6:00-8:30 and 16:30-19:00 intervals, from the total OD matrix of the day. Thus, the extraction of the walking, bike and private car OD matrices differ from the procedure executed for the public transport demand.

To extract the hourly OD matrices for walking, bicycle and private car demand, the COM interface is used, to introduce fast modifications to the model. A Python implementation is designed to create 24 empty matrices, representing each hour of a day. A link is created between those matrices and the matrices resulting from the combined trip distribution and mode choice procedure, which allows the creation of an hourly demand matrix for the aforementioned modes. Thereafter, the Regensburg model is rerun to estimate the OD hourly demand. Finally, the resulting OD matrices are exported as csv files.

To extract the hourly OD matrices for public transport, a different approach, in combination with aforementioned approach, is performed. In the original model, the PT matrices of the peak hours (i.e., 6:00-8:30 and 16:30-19:00) are calculated similarly to the matrices of walking, bicycle, and private car demand. Therefore, the procedure implemented for the three modes is also used to export the hourly PT OD matrices, for the same peak hours. On the contrary, for the off-peak hours (i.e., 8:30-16:30) it was not possible to replicate the same procedure, since it would change the complementary relation between off-peak, peak and daily PT demand. Thus, a different approach to segment the off-peak hours is needed.

In particular, in order to extract the off-peak hourly OD demand for public transport, a simplified approach using the statistics of "Mobilität in Deutschland" survey (MiD 2017) is performed. One of the main data gathered in the travel survey is the time profile of the trips. Based on the time profile published by the MiD, the total off-peak demand is segmented into 7 different time interval. Each time interval is the result of the product of the total off-peak OD matrix and the estimated perceptual share from the MiD dataset. At the end of this process, 19 hourly matrices are estimated for public transport and exported as CSV files. The external daily matrices, which include matrices corresponding to the segments of trucks, commercial traffic, external private car traffic and calibration, are provided as daily matrices, since no additional information is available

<u>Leuven</u>

The city of Leuven tested the implementation of a station-based, roundtrip bike sharing system for Park & Ride facilities outside the city. Using the methodologies and techniques developed in Level 2, in this scenario people originating outside Leuven city centre, will travel to parking lots outside the city of Leuven. Using the roundtrip bike sharing system, users could park their car and take one of the shared bikes for traveling the last mile(s) of their trip.

Input data for level 2 for the city of Leuven, included the following attributes that are available:

- The zoning system for the city of Leuven
- Car OD demand matrices. These include the demand from external zones towards the city centre. This is important, since these are the displacements that the bike sharing system is targeting.
- Car and bike road network.
- Selected area to locate the parking lots with accompanying bike sharing stations.

The methodological for the implementation of the bike sharing system in the city of Leuven follows the idea that users will park their cars in the parking lots outside the city's ring road and then using the BSS will travel their last mile of their trip. Using the OD matrices for the demand from external zones to the city centre, the first step of the methodology is to set a number of candidates called P (parking lots). Then the OD pairs are transformed into O-P-D pairs, by minimizing both the O-D and P-D distance with higher weight to be implemented on the P-D side, since that is the part of the trip that is of importance for the BSS. From the set of candidate locations P, a subnet of locations P is selected. The subset is the one that minimizes the maximum or average P-D distance, the distance of these locations to the road network (related to the O-P part of the accessibility of the parking locations) and the number of locations. Finally, a number of predefined locations can be used as constraints in order to meet the needs of the city to include specific parking locations into the investigation.

3.3 Improvements and modifications

As part of MOMENTUM project, the implementation of each of the three Levels was first evaluated in the city of Thessaloniki, which is used as testbed. After this initial analysis then, each city partner has tested the DST based on their own case study. Guidelines describing each step of the testing procedure of each level were sent to the city partners. After the testing process was completed, feedback with comments and suggestions for further improvements of the DST were proposed. In level 2 changes were focused on the online version of the tool. Due to the different sources of input data that are available in Level 2, pre preparation of input data was important to be made. Visualization improvements followed after feedback received. In this sections of the document, improvements and modifications regarding level 2 of the DST received and implemented, are described for each case study.

Thessaloniki

Once the testing of Level 2 in the city of Thessaloniki was examined, improvements of the DST are suggested. Notes and changes to be done for further improvement include the following actions:

- In the second version the extraction of a JSON file with the location if the stations will be available. This file will also contain the capacity of the stations in the vehicle-sharing case.
- The set of final stops will be easy to manipulate. As some of the stations may not be in a suitable position the user of Level 2, will be able to manually resettle the location in a feasible place.
- The user could be able to decide if some stop candidates should be included in the final solution as special points of interest.
- The last section will be enriched with more results extracted from simulation.

Madrid

The level 2 was tested for a district in Madrid, were the BiciMAD service has not been implemented yet. After the initial trials and tests, the following updates were proposed:

- The tool works step by step and when a step has passed, it is not possible to come back to change parameters from previous steps; the entire process has to be re-started from the beginning. This has been corrected and now the tool is more interactive.
- Whenever the files provided to the system do not present a correct format, the tool provided a generic error message that prevented regular users to debug their own files. This has been updated to show more detailed logs that help the user to debug their data files.
- Some of the maps displayed through the configuration process were not correctly centred within the area provided. This was a minor issue that has been fixed and now the map centres at the given area.
- Some of the results and visualisations (maps) lacked descriptive information to inform of what is being observed and reported. Now the application provides such information in all places.
- The functionality to download of the results in GeoJSON or JSON format was proposed to facilitate the usage of Level 2 into the MOMENTUM pipeline and has been already implemented, so any user can download the results of the tool in GeoJSON format.
- Some refinements were suggested to improve and simplify the documentation of the tool. This was done at the application level, by suggesting the introduction of information buttons that explain each

parameter and output element and at the documentation level by suggesting the elaboration of a user manual that limits technical details for the user of the Level 2.

Leeuven

In the city of Leuven, a new approach of Level 2 was tested. As the methodology differs, the validation and calibration procedure of the BSS in Leuven can be assessed by an already implemented survey on potential Park and ride location for BSS. In Figure 11 below, the location of those suggested locations can be seen.

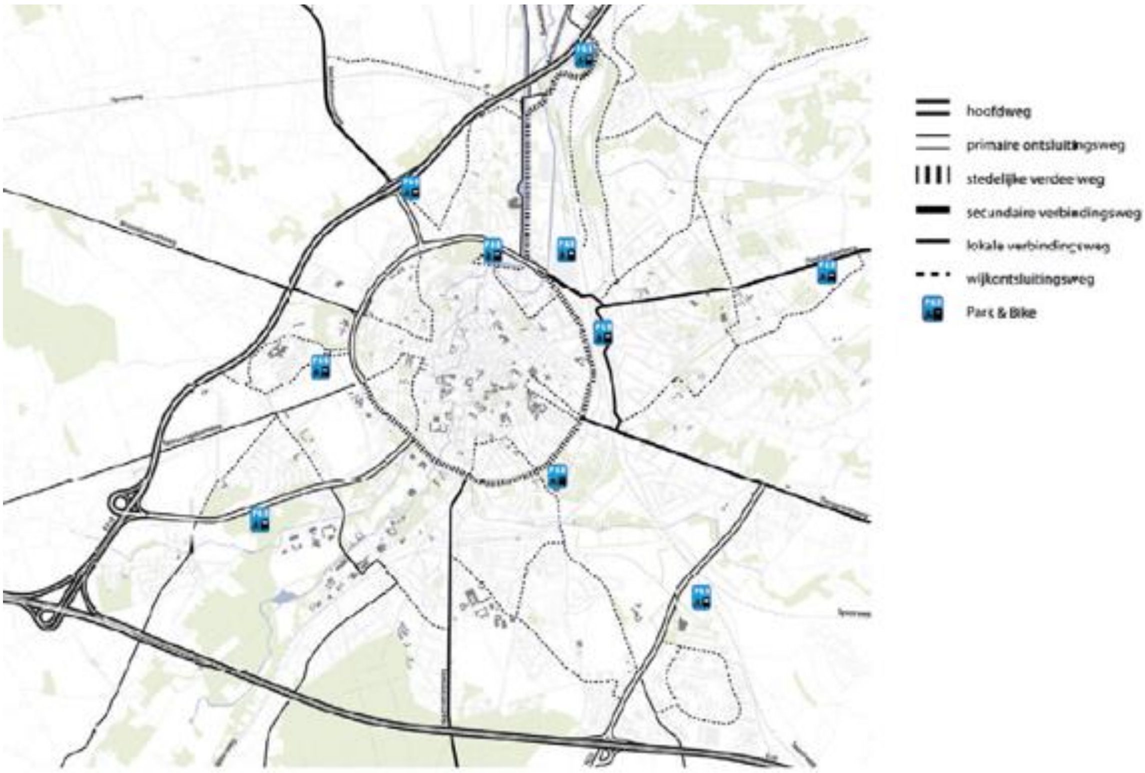


Figure 11: Existing park and ride locations for the city of Leuven

The potential added value of the testing of the BSS in the city of Leuven, is that investigating this approach of the service will expand the case studies for which Level 2 can be used. The different approach and the new possibilities leave room for improvements of this approach in order to be applicable in similar cases and cities.

4 Calibration and validation of DST -Level 3

4.1 Introduction

The last step of the multilevel decision support tool involves a comprehensive analysis of the examined district by modelling the transport scheme of the selected city. Transport modelling can be a powerful tool in understanding the potential traffic impacts of the proposed solutions. It can also enable the development and evaluation of different transport planning strategies and interventions aiming to increase sustainability with emerging mobility services, mitigate congestion and environmental impacts.

The interactive decision support dashboard, the policies under consideration and the KPIs are tailored to the specific requirements of each case study. More information about the KPIs to be produced can be found in the D5.2 “Interaction Support Toolset”. The implementation in the city of Thessaloniki worked as a testbed for the implementation in the rest of the cities. The new toolset is implemented on top of the existing mobility ecosystem, which holds a variety of data analysis and simulation tools, allowing the cooperation of public and private institutions. It has become a real-life conditions testbed for innovative mobility solutions.

The nature of the methodological stream of Level 3 is based on the investigation of the transport model of the city examined. In this level of the MOMENTUM project, comprehensive transportation information is used in order to examine the potential impact of emerging mobility services, based on methodologies described in WP3, WP5 and D5.1 alongside with the questions and needs of the city partners in WP2. Hence the implementation of Level 3 is a more complicated procedure and cannot be fully automated, as the previous levels (Level 1, Level 2). Validation and calibration of the procedures of Level 3 were integrated by the scientific partners and the city partners. The methodologies and the calibrating of the used data are described in the next section. Finally, in the online version of the DST, in Level 3 user need to proceed with the implementation offline and then using the visualization and analytical tools of the online version, and assess the produced results.

4.2 Application of WP4 to Level 3

To achieve the general objective of MOMENTUM project, is to develop new modelling approaches that are able to ascertain the impact of emerging mobility concepts and solutions. This means that changes required to incorporate emerging mobility solutions into strategic transportation models, both in terms of supply and demand, have to be formulated and explanatory and predictive models have to be constructed. Deliverable 4.1 describes the models developed in MOMENTUM, which are able to capture and mimic user interaction and behaviour with emerging mobility services in the strategic transport models, both in terms of supply and demand.

An intermediate modelling approach was formulated (for more information the reader should refer to D4.1 “New Transport Modelling approaches for Emerging Mobility Solutions”) which integrates the principles of agent-based approaches within the traditional four-step approach, providing an opportunity for cities to evaluate and integrate shared mobility systems and form long term planning strategy

The developed models and algorithms were described in detail in Deliverable 4.1. and Deliverable 4.2 described the technical characteristics of the developed solutions, which differ in terms of algorithms as well as programming languages that have been used. As mentioned in Deliverable 4.2 not all the developed modules are open source or developed with the same technologies, hence, an automatic integration of those modules is not feasible. Additionally, some of these models are directly implemented into the commercial transport modelling software Aimsun Next so they need to be executed independently. Nevertheless, the outputs from those models are valuable input to state-of-the-art simulation software in order to enable the evaluation of the strategic planning for shared mobility services. Another reason why it may be infeasible to integrate all the modules into a single tool is that most of the models need to be calibrated with data from each specific city whose availability and quality may differ across different use cases.

4.3 Thessaloniki Case Study

4.3.1 Introduction

The main objective of Thessaloniki case study is to **improve the planning and decision-making process** for the introduction of resilient sustainable mobility schemes, with emphasis on the **adoption of DRT, ride-sharing and vehicle sharing** (micromobility, bike & electric car) mobility solutions towards MaaS in the agglomeration. Other equally relevant objectives are the development of techniques which can **facilitate proofs of concept** of new mobility schemes and the improvement of the **use of innovative data sources** (Floating Car Data, point-to-point detections, social media, etc.) in the transport modelling process.

The above services will be delimited geographically in order to better fulfill the mobility requirements of the citizens while reducing the operation costs for the operators. The study areas where the different services will be examined can be seen in the picture below. The proposed services evaluated in the project are described below:

- DRT is expected to have better performance in the surrounding of the agglomeration, where population density is low. It can be based on flexible bus lanes or on a ride-sharing service where taxis will feed the perimetral bus stations.
- Ridesharing has been already implemented in the framework of the GALILEO4MOBILITY project in 2019, providing taxi-sharing services to people living in suburban and peri-urban areas (1 of each) towards the city center and back home.
- Vehicle-sharing schemes is expected to perform better between the city center and the suburban and peri-urban areas for electric cars, while for bike sharing and micro-mobility it may work better if limited to the city center and the suburban areas only.
- Bundling all the above services together and engaging the PuT authority responsible for the buses and the metro, a door2door MaaS service could be offered in Thessaloniki.

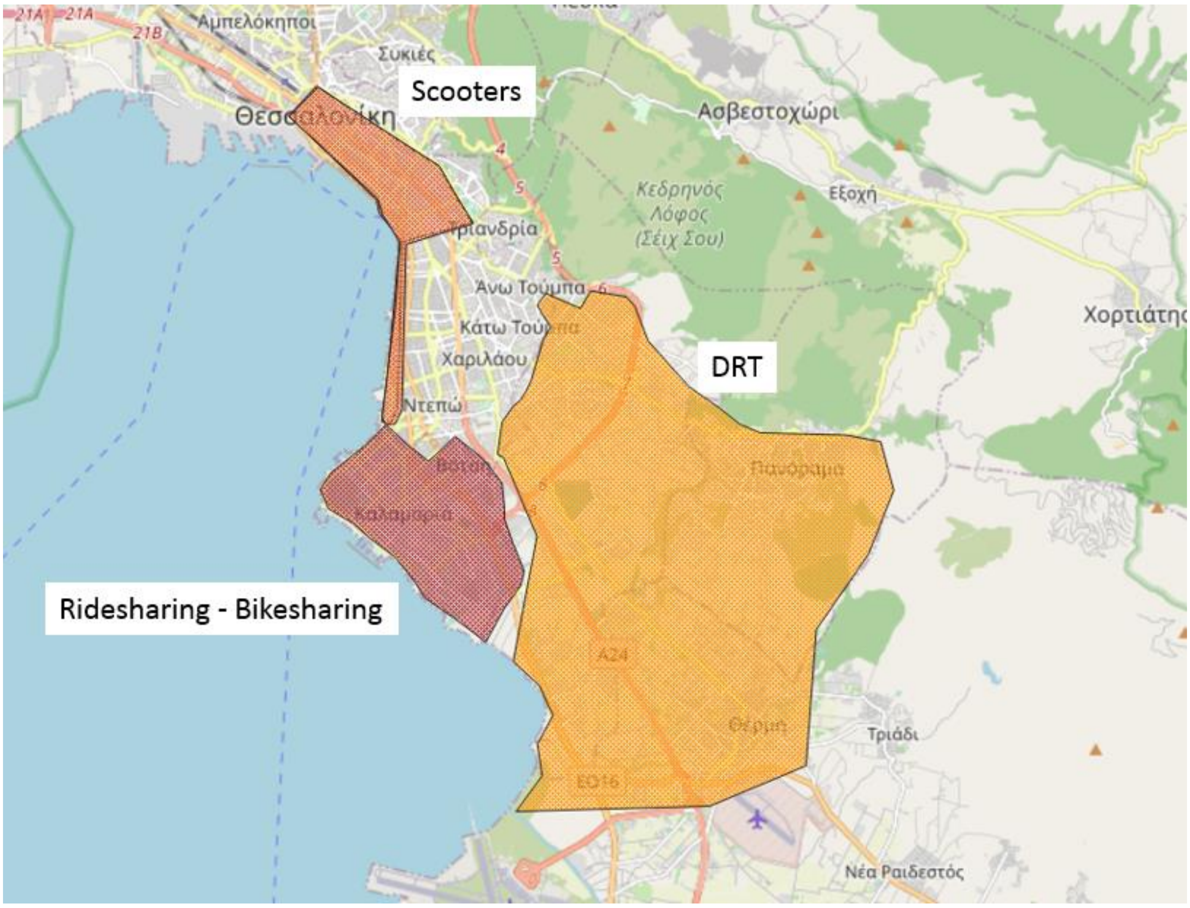
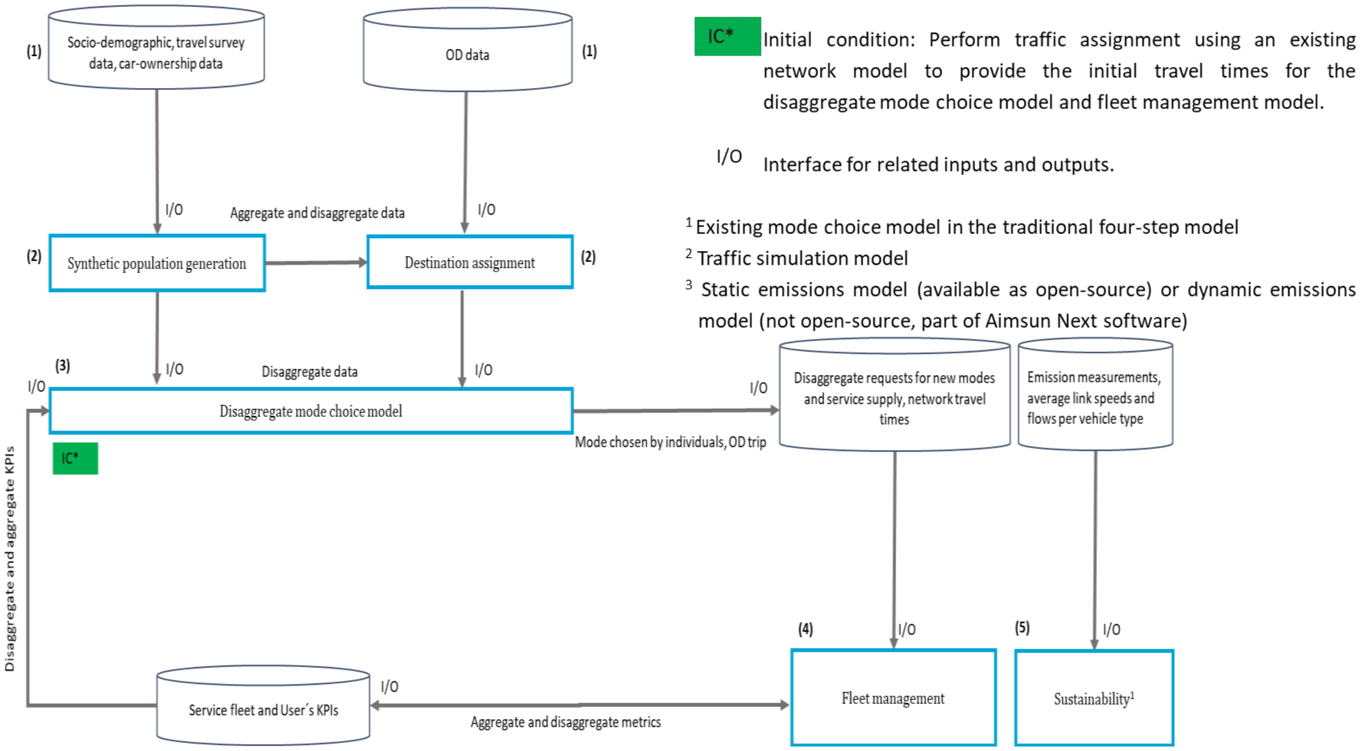


Figure 12: Areas to be tested in Thessaloniki case study

4.3.2 Local Workflow

Results from level 2 of the DST tool has been used to obtain a set of optimally placed candidate locations for stations within the selected district's boundaries. The methodological approach that is followed is described in

Deliverable 4.1. When the demand penetration is low, the hypothesis is that the network travel times will not change with the introduction of the new demand for shared mobility services. Specifically, if the demand for shared trips is below a pre-specified threshold, the network travel times obtained from a traffic assignment, or any other available data source, can be considered as fixed in the implementation and evaluation of the models that utilise travel time information. These models are the disaggregate mode choice model as well as the fleet operational algorithms and the simulation platform for shared mobility services. More information about the low penetration are described in the Deliverable 5.1.



4.3.2.1 Modification of Transportation network

CERTH/HIT has developed a **4-step multimodal macroscopic traffic simulation model of the detailed large-scale network of the agglomeration of Thessaloniki** since 2010. The model is developed in VISUM 15.0. The model has been continuously updated with data –concerning both the supply and the demand side - collected through various research and national projects, the latest of which being the Sustainable Urban Mobility Plan of the Municipality of Thessaloniki (2017-2019).

Based on the existing VISUM model in Thessaloniki, CERTH produced an integrated transportation road network model in the AimsunNext traffic simulation software in order to utilise the shared mobility service simulation platform Aimsun Ride which designed as a plug-in inside Aimsun Next. . All the necessary transport features from the VISUM model where imported into the new Thessaloniki's Aimsun Next model. The road network and related features (links, nodes etc.) and travel times were obtained from the VISUM model and are considered fixed during the simulation of shared mobility services, based on the scope of the project and Thessaloniki's case study which is to plan and evaluate the shared mobility services at a strategic level. In addition to the road network information, the disaggregate demand derived from the disaggregate mode choice model as well as information about the fleet planning and operations are required for the implementation and evaluation of emerging mobility services in Aimsun Ride. This is achieved through a suitable interface between Aimsun Ride, the external fleet planning and operational models to make the interaction between the three models feasible.

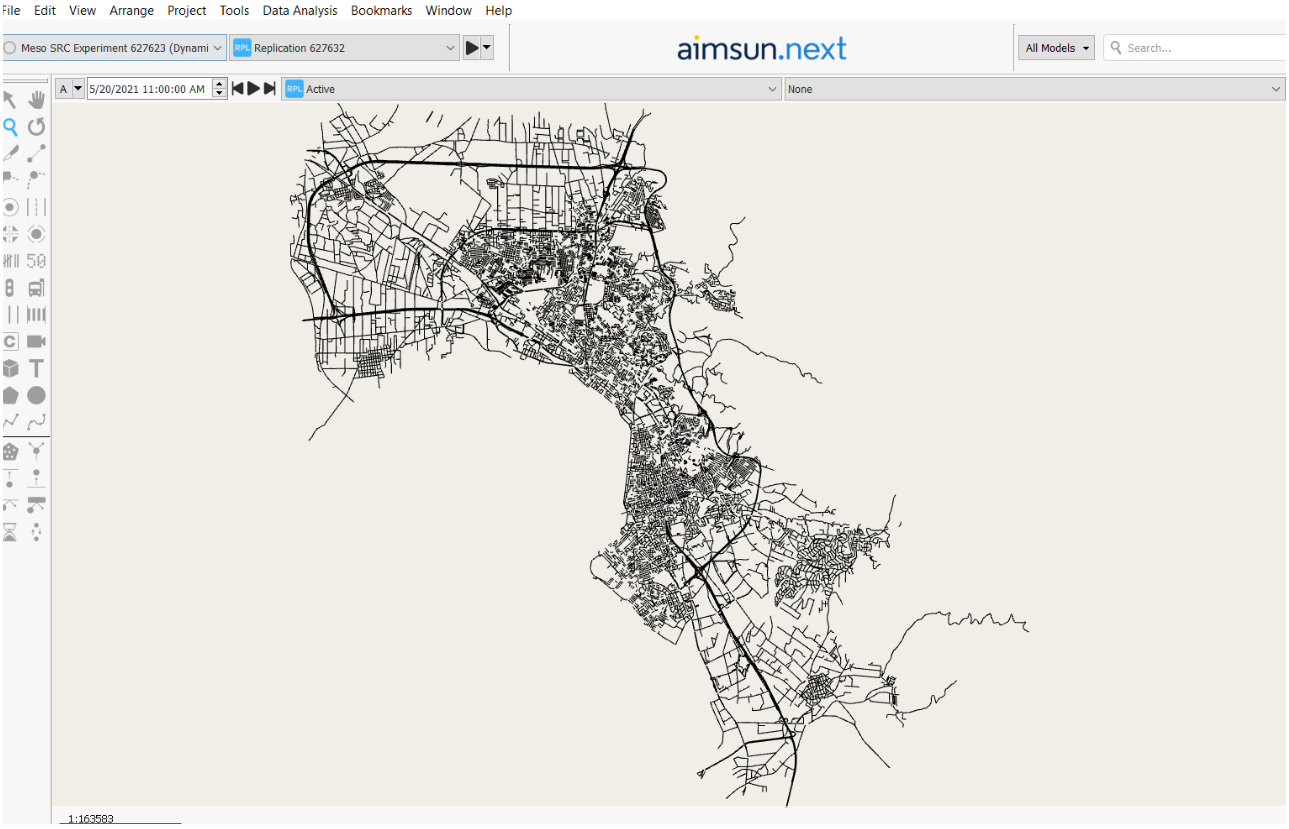


Figure 13: Thessaloniki's network in Aimsun Next software

4.3.3 Models´ implementation and calibration

4.3.3.1 Demand model

The most recent (2017) main data sources for **demand** estimation included telephone surveys and stated preferences surveys, as well as traffic counts in 40 network points (on a 24-hour basis) and 20 road intersections (data provided by the Municipality of Thessaloniki). The daily resulting OD matrices per mode have been temporally segmented in the peak hour interval (08:00 – 09:00) based on the profile provided by previous RSS survey and the most recent household survey. Approximately an 8% of the total daily demand is attributed to the morning peak hour.

On the private transport **assignment** (cars and taxis), the user equilibrium traffic flow estimation, based on **Wardrop's user equilibrium principle**, has been solved with an implementation of the Linear User Cost Equilibrium algorithm, terminating at pre-specified goodness-of-fit criteria for the resulting traffic volumes. The public transport assignment was based on the bus lines headways. The **zonal system** of the model consists of 339 traffic analysis **zones**, 328 of which are used for describing the metropolitan area of Thessaloniki, while the rest are external zones. Indicatively, the Municipality of Thessaloniki is covered by 125 zones. A total of 4.256 **connectors** are used for connecting zones to physical nodes of the road network, according to their accessibility index, avoiding connections with nodes of high hierarchy links.

The aggregated demand for conventional modes was available in the case of Thessaloniki. Thus demand for shared mobility services is obtained from the synthetic population module in order to generated disaggregate trips to be used as input to the disaggregate mode choice model based on the methodologies described in D4.1 and D5.1. Following, the estimated disaggregate demand for the shared systems along with data and information related to the request characteristics, service and network supply are fed into the fleet management model, to optimise the trip plan solutions and simulate the operations to serve the demand for the shared services. Further information about the synthetic population and the method of model choice model followed, will be analysed below.

4.3.3.2 Synthetic population

The synthetic population generation provides synthetic individuals, usually characterised by general socio-demographic attributes. It is deployed in order to generated disaggregate trips to the disaggregate mode choice model. Synthetic individuals are generated based on the disaggregate OD demand matrices and socio-demographic data that were collected and prepared according to the requirements of the synthetic population method followed in the software of PopGen. A base synthetic population is generated, and a destination choice is assigned to each synthetic individual.

Attributes related to the profile of the individuals that chose a shared mobility service for their trips have been included in the synthetic population. In the case of Thessaloniki, data sets share common attributes with the same definition and categorisation and are considered sufficiently correlated with the new attributes of interest. Variables and their categories were used as input in the software PopGen for the synthetic population module of the city, aligned with the needs of import data in the next step of the mode choice model.

In the case of Thessaloniki, values from stated preference and telephone surveys for a sample of around 11,000 participants in 2017 were used, alongside with demographic statistics obtained from the Hellenic Statistical Authority for the extended region of Thessaloniki. Data from the census and surveys were available at different geographical resolutions. Region data were available at a high (aggregated) resolution, at TAZs or region, while geo information at finer geography levels (city blocks). Thus, in the city of Thessaloniki the upper Spatial Resolution included disaggregated detail data while the lower Spatial Resolution included more aggregate detail data, based on the nature of the surveys this information was derived from. Socio-economic data were categorized based on the analysis structure of household and person. In the first one household size, number of cars and income are included while on the person category information about the age, gender, education and employment status were taken into account. It is important to mention that the format of the categories included in the investigation were selected based on the input data of the mode choice model, which is the next step of the case study of Thessaloniki.

Data from the upper and low resolution of the surveys in Thessaloniki, needed to be integrated in order to be used by the PopGen software. In extension to PopGen, the categories were designed in align to the format of input data of the mode choice model to be performed in the next step of Level 3.

Table 1: Categories of the information derived from surveys in Thessaloniki

Household		**Income**			**Number of cars**	
1 member	1	<10.000	1	Low	No Car	0
2 members	2	10.000-20.000			1 Car	1
3 members	3	20.000-30.000	2	Medium	2 Cars	2
4 members	4	30.000-40.000			3 Cars or More	3
5 members and more	5	40.000-50.000	3	High		
		>50.000				

In the figure below, is presented the different levels of the lower and upper resolutions used in the case of t the city of Thessaloniki.

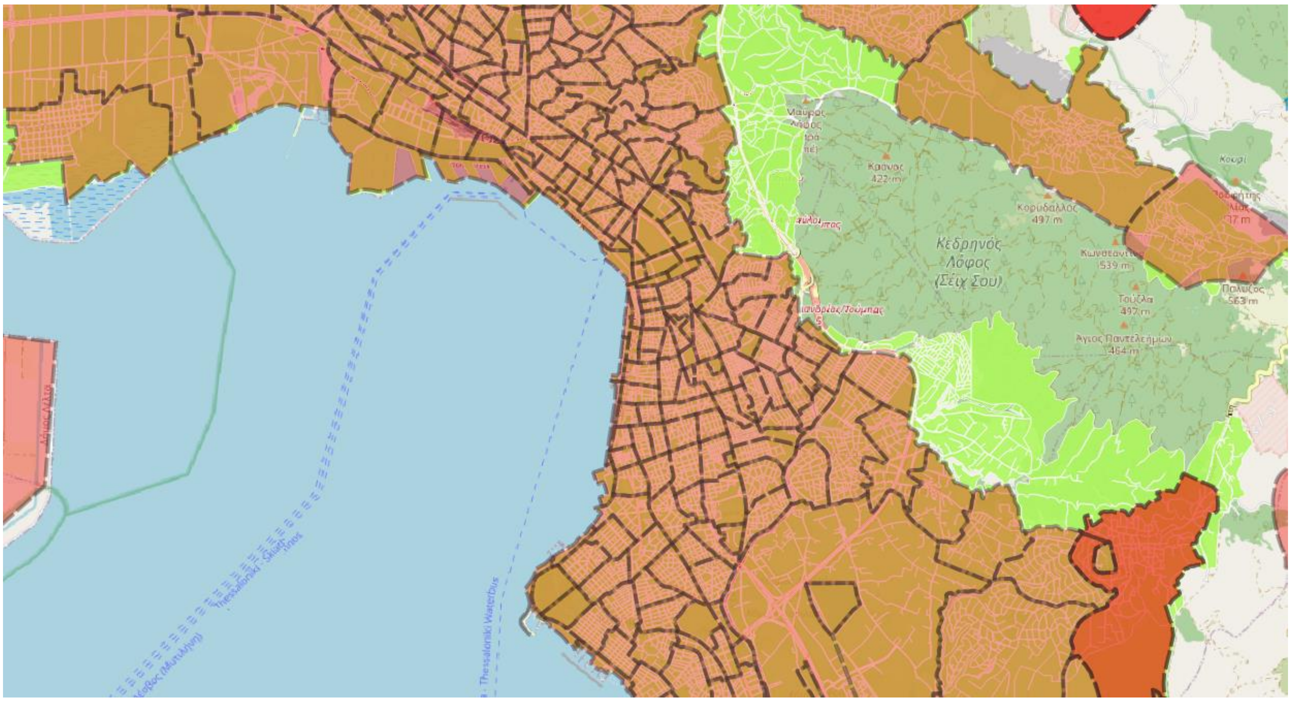


Figure 14: Upper and Lower spatial resolution in Thessaloniki

4.3.3.3 Mode choice model

Input for the mode choice model is the trip travel times between origin and destination zones that is assigned to each individual. The travel times are provided as skim matrices to the mode choice model after performing a traffic assignment using the existing travel demand model of the city, which represents the demand for conventional modes. The execution of the traffic assignment model is an initial step, which defines the starting point for the integration of the framework.

The results from the synthetic population is provided as input to the disaggregate mode choice model, along with other model parameters to estimate the mode choices for shared mobility services and conventional modes. Another necessary input for the mode choice model is the trip travel times between origin and destination zones that is assigned to each individual. Historical travel times obtained from the VISUM static assignment model or based on the available travel time observations were used in the disaggregate mode choice model and in all fleet management scenarios. Coefficient values used for Thessaloniki have been selected from the available values in the corresponding directory in the MOMENTUM GitHub repository.

4.3.3.4 Fleet management model

The estimated disaggregate demand, for the shared systems along with data and information related to the request characteristics, the service and network supply are fed into the fleet management model to optimise the trip plan solutions. The fleet management model, consists of the methods to derive the planning, operations and the simulation platform of the shared services. Finally, the derived trip plan solutions to serve the demand requests are deployed and simulated in order to assess the operation of various scenarios related to examine shared mobility services. The pre-determined KPI´s (see D5.2 for more information about the KPIs) and traffic metrics obtained from the fleet management model can be further provided as updated input to the disaggregate mode choice model to repeat the estimation of the modal shifts. Finally, post processing is carried out to calculate emissions by receiving output data from the traffic assignment model.

In order to estimate the demand for the shared services to be tested, results from the Level 2 estimation are used. Based on the FCD provided, stops for the vehicle sharing and DRT services will be used. To generate an aligned testing bed in the case of the city of Thessaloniki, days and time windows of the transport model will be used. The station based shared mobility service simulation will try to satisfy trip requests set. If number of requests is not satisfied with the available fleet based on the constraints, then the disaggregate mode choice model will rerun and after that the simulation reassignment will follow.

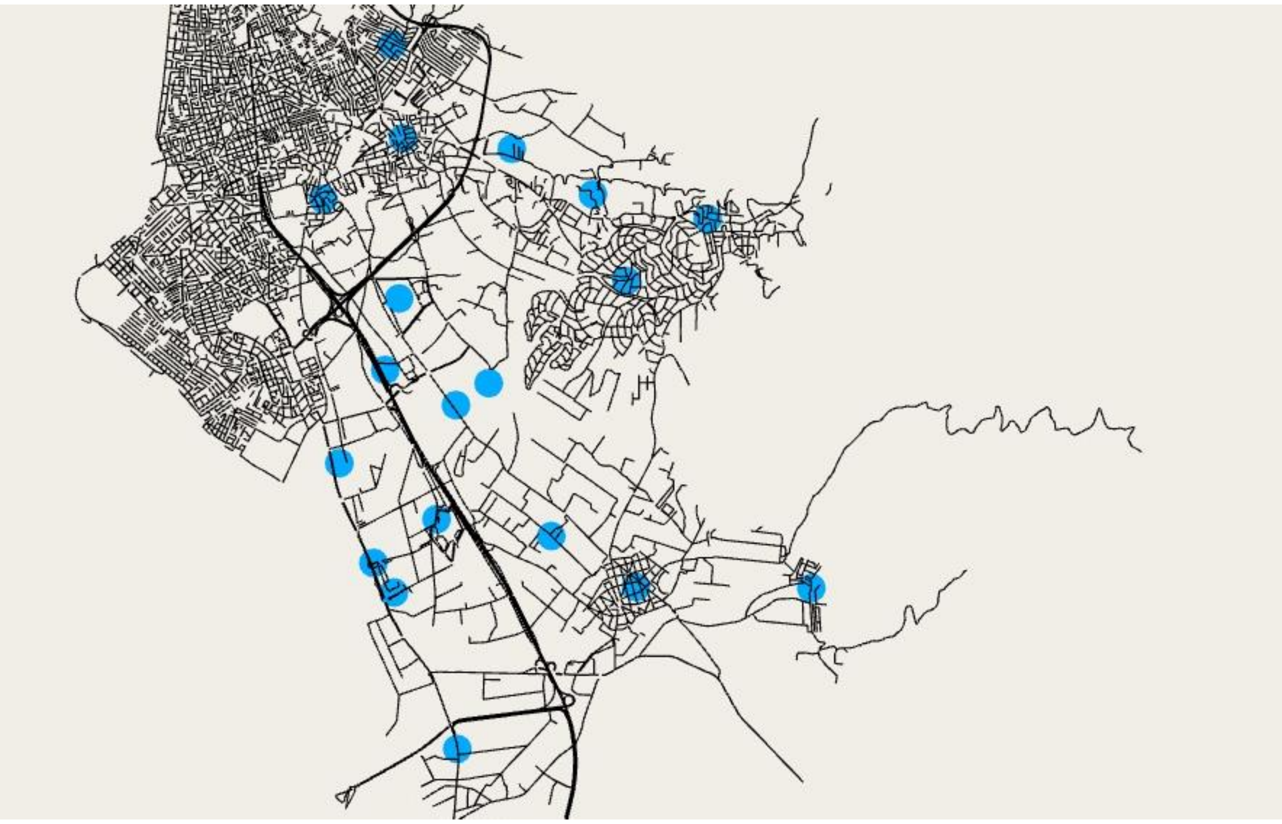


Figure 15: DRT stops in the examined area, in the city of Thessaloniki

4.4 Madrid Case Study

4.4.1 Introduction

The geographic boundaries for the simulation is obtained from the regional transport authority of Madrid (CRTM) and potentially adapted for districts that are not completely urbanised.

For level 3, Madrid case study will focus on the simulation of BiciMAD shared mobility service in a district where it has not been deployed yet: Villa de Vallecas. This district is one of the outermost districts of Madrid city with a population of approximately 110,000 inhabitants. The district has six metro stations, two train stations and several lines of the city bus service. Villa de Vallecas was selected as the focus district for the third research question of the Madrid case study (See Deliverable 2.2 Specification Test Cases for reference).

The main goal of the simulation experiment is to understand the potential impact of the implementation of shared mobility within the district. In fact, Villa de Vallecas is a district where no shared mobility service has been deployed yet. Villa de Vallecas is very well connected within the district and with other parts of the city through public transport services. Hence, this case study will allow to address other research questions such as the role of shared mobility within the public transport ecosystem (complement or compete against).

4.4.2 Local Workflow

Shared mobility demand data in the district will be predicted using the data-driven shared mobility demand estimator module described in Deliverable 4.1. In this experiment two penetration scenarios will be tested: low and high penetration. The current situation corresponds to low penetration and so are the predictions obtained from the data driven model. For the high penetration case, a growth factor will be applied to the demand prediction to augment the demand. For both scenarios 4 different day types will be evaluated: summer weekday, summer weekend, non-summer weekday and non-summer weekend. Figure 16 illustrates the high-level scheme of the proposed simulation.

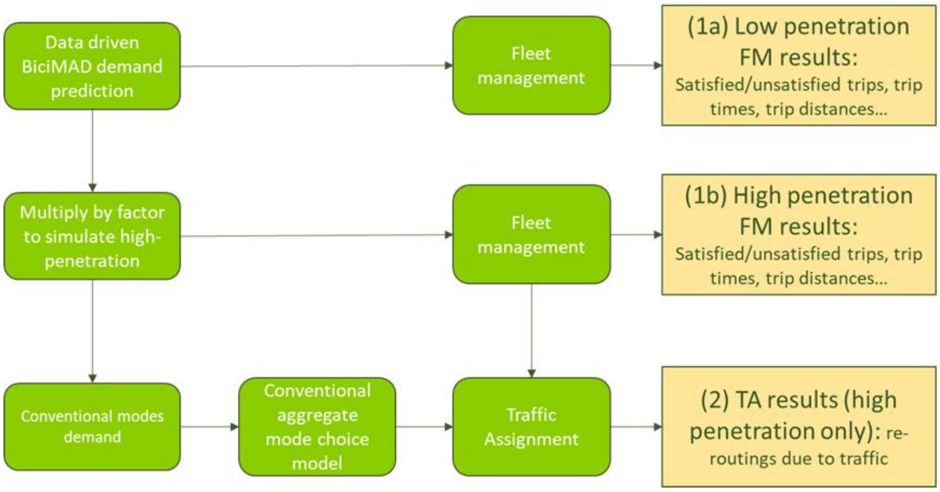


Figure 16 Scheme of the proposed simulation experiments

Shared mobility demand information is obtained from a district prediction provided by the data-driven shared mobility prediction module developed as part of the MOMENTUM toolset (See Deliverable 4.1). This demand model takes as input the overall mobility, the land use and weather observations in each date of study within the areas of the district. In order to cover various temporal scopes, the predictions are computed for four types of days: summer weekday, summer weekend, non-summer weekday and non-summer weekend. These reference days have been obtained by averaging the input variables (weather and overall mobility OD matrices) of a subset of days: Tuesdays, Wednesdays and Thursdays for weekdays and Saturdays and Sundays for weekends

The level 2 of the decision support tool has been used to obtain a set of optimally placed candidate for stations within the district's boundaries (as described in Deliverable 4.1).

4.4.3 Models implementation and calibration

4.4.3.1 Data-driven demand prediction

To generate the shared mobility demand estimation, the data-driven shared mobility demand estimation module of the toolset is used (See Deliverable 4.1). Such module consists of a regression model that estimates the expected shared mobility demand per OD pair as a function of the general mobility (mobile phone OD matrices), land use and weather information. To generate the predictions associated to each day of study, a set of average days has been created by averaging the associated input variables of a small subset of days (15th, 16th and 17th

October 2019 for non-summer weekdays, 19th and 20th October 2019 for non-summer weekends, 16th, 17th and 18th July 2019 for summer weekdays and 20th and 21st July 2019 for summer weekends).

The prediction provided real values which should be converted to real integer trips. For the conversion, the real values are used to build a probability density of a beta-binomial distribution to assign a probability of a trip to occur.

4.4.3.1 Fleet management

Two models from the fleet management module have been used within a simulation environment to generate results:

- Fleet management algorithm with rebalancing strategy: This sub-module is applied to manage the shared mobility service, so the provided demand is covered by the system. Among others, this module will provide rebalancing strategies and routes to optimise operation teams while maximising the number of requests served.
- Station-based shared mobility service simulation (Aimsun Ride). This sub-module is used to simulate the actual execution of the shared mobility service requests (predicted demand) for a given state of the service (In which stations are the different vehicles parked). This algorithm will try to satisfy all trip requests (demand) and will register satisfied/unsatisfied requests. For further reference, Deliverable D5.1 “Enhancement of Transport Simulation Frameworks with Models of Emerging Mobility Solutions” might be consulted.

4.4.3.3. Expected results

The expected results from the simulation are oriented to the analysis of the effects that shared mobility will have when initially deployed. For that purpose, the analysis will target the following results for both low and high penetration scenarios:

- Fleet management outputs: the results from the fleet management sub-module will provide information regarding hotspots (places with pour shared mobility coverage) and the detection of other interesting areas within the operation boundaries.
- Request completion: the simulation of the shared mobility service will further provide the figures for satisfied and unsatisfied requests. This will help to correctly dimension a hypothetical service to be deployed in the area. Furthermore, the exercise will allow to detection of areas with high rates of unsatisfied requests within the district. This could inform on the relation of the shared mobility service with the public transport network, opening opportunities for improvement on both sides.

Finally, for the high penetration scenario, the traffic alterations are caused due to a very large number of bicycles entering the road network of the study area to be analysed. In this case, the objective of the analysis will be the identification of congestion situations and other traffic alterations due to the penetration of bike-sharing and the potential impact they could have on public transport systems (bus lines) and private vehicle usage.

4.5 Regensburg Case Study

4.5.1 Introduction

The main objective of the Regensburg case study is to have a reliable model for deriving scenario outputs and guiding evidence-driven policy input by integrating the new mobility services into the existing model. The city has been very active in exploring various novel mobility services and concepts. One of the largest ones includes one-way bike-sharing, with about 600 shared bicycles to start operating soon. The existing car-sharing system is planned to expand, and an Autonomous People Mover (APM, shuttle with a capacity of 6 people) along a predefined area in a business park outside of the city centre will also be introduced. Therefore, the case study, as mentioned in D2.2, will focus on the impact of bike-sharing, car-sharing and APM services. Besides the testing of these three services, implementation of dedicated lanes for PT (a policy question) will also be explored, along with investigation of traffic emissions in the city. The aim of this section is to design the modelling framework for the case study, based on the initial scope defined in D2.2, which will be later refined in WP6.

4.5.2 Local Workflow

Currently, Regensburg uses a conventional 4-step model, implemented in the PTV VISUM software, which follows an aggregated static modelling approach. The model uses a specialized demand generation method from PTV, which is a tour-based approach and is called VISEM. This approach is a different approach to the traditional 4-step model, since it models activity chains based on the different person groups in the model and their trips. Within this approach, the trip distribution and mode choice processes are implemented as a combined step and further this combined step is inter-locked with trip generation step. On the one hand, all these add additional complexity, which makes the case study of Regensburg different from the rest. On the other hand, VISEM enables modelling of tours for every agent discretely. Thus, individual trips can be generated with some assumptions. Taking all these into account, a modelling schema has been prepared for the Regensburg case study, which is shown in Figure 17.

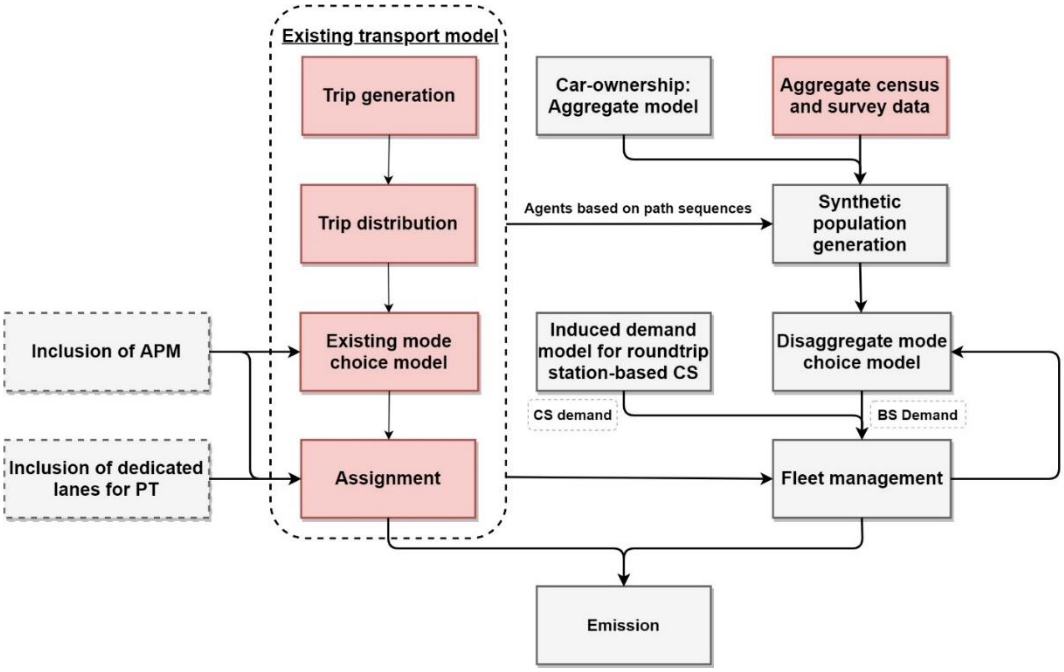


Figure 17. Modelling schema for the case study on Regensburg

4.5.2.1 Modification of the VISUM model

The case study on Regensburg includes modelling of APM and dedicated lanes, both of which usually require a microscopic modelling approach. Nevertheless, a methodology has been devised for each of the two. These approaches will be included as modifications in the existing VISUM model. Although an initial analysis shows some positive results, the implementation of these approaches (which will happen as part of the case study implementation, later in WP6) is a trial and if successful, this may help several other cities to adopt the paradigm of Regensburg's implementation in Level 3.

4.5.2.1.1 Inclusion of APM

The APM will be included through the modification of the existing Regensburg model, rather than through an external component. Concerning the service specifications, the APM line comprises of seven stops, along a circular path in the street named "Im Gewerbepark" (See Figure 18). The mover line is connected to nearby bus lines 5, 8, 36 and 37 within walking distance. The service is programmed to be operated from 11:00 to 15:00 on weekdays, with a headway of 10 minutes.

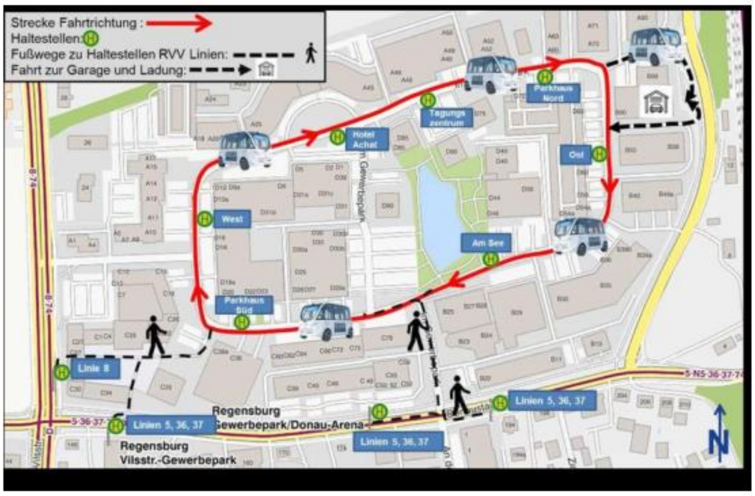


Figure 18. APM Line. Source: Regensburg office

With regards to the introduction of the APM in the model, Figure 19 depicts the methodology that is followed. The first modification in the model is the inclusion of the mover to the demand segment of public transport (ÖV). The APM system is defined as a single unit vehicle, with speeds of 12 km/h and capacities of 12 people per vehicle; based on the autonomous vehicle data from “Ollie”, an APM developed by Local Motors in 2016. Thereafter, the stops and lines are introduced into the network, as seen in Figure 18. Afterwards, the connectors are imported for the PT (Public Transport) line, connecting the stations with the centre of the TAZ ‘2308’. Finally, the timetable is generated based on the service time from 11:00 to 15:00, with a headway of 10 minutes.

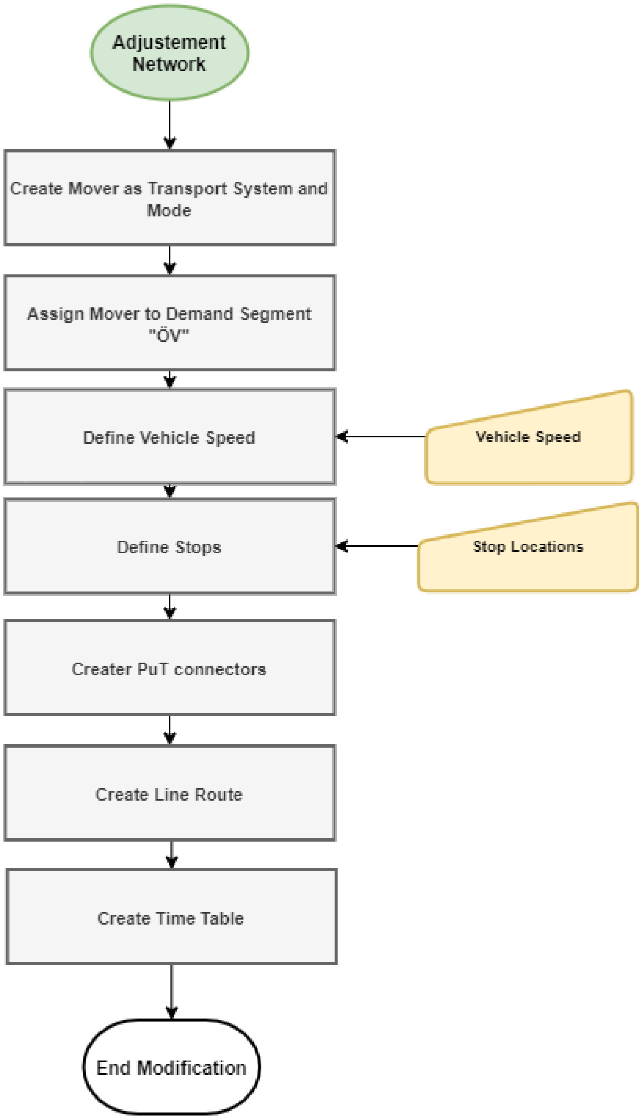


Figure 19. APM introduction flowchart

After the inclusion of the service in the simulation system as part of PT system, the next step is to model the demand for the APM. Due to the fact that the mover line belongs to a single TAZ (2308), the types of trips, in relation to the TAZ, must be considered. Traditionally, the trips can be classified, by their relation to the TAZ, as external and internal trips. For internal trips, the implementation of the parameters for the mover has been a challenge. The original Regensburg model relies upon some external inputs, to model the internal trips. Specifically, the combined trip distribution and mode choice step relies on a variable known as "BINNEN FAHRTZEIT_ÖV".

The variable "BINNEN FAHRTZEIT_ÖV" corresponds to the average travel time of an internal trip, when using public transport. This variable mainly influences the utility of the public transport mode. Especially, for internal trips, the mode choice utility for public transport is entirely based on this variable. According to the information from the city of Regensburg, the value corresponds to the closest distance to a neighbouring stop, multiplied by an unknown scaling factor. Thus, the scaling factor is the key in modelling the internal traffic demand for the APM. A linear regression model is estimated to ascertain this scaling factor.

4.5.2.1.2 Inclusion of dedicated lanes

The other implementation to be discussed for Regensburg is the creation of an approach, which would help to evaluate the implementation of dedicated bus lanes in the city. Evaluation of such implementations are usually based on microscopic simulation approaches. Thus, the creation of an approach to model dedicated bus lanes in aggregate transport model is a challenging task. The difficulty of this implementation lies in the following two fundamental challenges:

- How to model the interaction of PT and private vehicles in the Regensburg VISUM model? In general, PT is modelled based on timetables and hence, not loaded into the road network for travel times, as done for the private vehicles.
- How to represent the dedicated bus lanes in VISUM?

To tackle the aforementioned barriers, the procedure sequence and network characteristic are modified in VISUM. In the following paragraphs, the modifications are described.

4.5.2.1.2.1 Interaction of PT and private vehicles

By default, in the Regensburg model, the volume of PT vehicles is not integrated in the volume delay function, which describes the congestion in a link. With the aim of integrating PT volumes in the volume delay function calculations, the first step is the modification of the "Base Volume" in the assignment procedure. According to the PTV VISUM manual, the "Base Volume" is used to consider the volume of vehicles loaded into the network, before the private vehicle assignment (PTV Group, 2020). Therefore, the traffic assignment step has been modified, to allow extraction of the base volume from a link attribute. In the current case, the base volume is calculated based on the "Number of service trips" (i.e., the network will have a base volume according to the scheduled public transport vehicle trips). Through this procedure, the modelling of the influence of PT volumes on the private vehicles is addressed. Nonetheless, the barrier to the influence of the private vehicles on PT travel times is still unaddressed.

The Regensburg model uses a timetable-based approach for the assignment of the PT vehicles. As a consequence, the travel time in the lines of public transport is dependent on the established speed for the transport mode. Thus, the travel times of public transport is independent of the volume of traffic in the transport network. To introduce the influence of private vehicles on the travel times for PT, the special function "Set run and dwell times" in VISUM is used. This PTV VISUM functionality enables transfer of the link travel times to the PT lines. After using this function, the PT travel times are calculated using the original PT assignment model, but with consideration of link travel times.

With the modifications above that are implemented in order to simulate a mixed traffic simulation, the demand modelling procedures are affected. Consequently, the model does not represent the real traffic in Regensburg. Thus, a recalibration of the model is performed. For the recalibration, the OD matrices from the original base model (the model without any modification implemented) is used. The recalibration procedure adjusts the trip length distribution for private vehicles to coincide with the OD matrix of the original model. Finally, the calibrated matrix is provided to the assignment procedures and the final traffic flows of the model are computed.

With the aim of evaluating the quality of the calibration, two aspects are considered. The new modifications influence the combined trip distribution and mode choice step. Thus, both the trip distribution and mode split after calibration are analysed. In order to quantify the trip distribution, the GEH statistic was used (Equation 1), as described by Duraku et al. (2019). Moreover, the acceptance criterion is to find a GEH value less than 5 in 85% of the OD pairs (Duraku et al.,2019). In the current case, the resulting GEH calculations show that 99% of the OD pairs have a GEH value of less than 5 (See Table 2). Consequently, the model was considered calibrated, with respect to trip distribution.

$$GEH = \sqrt{\frac{2(O_i - M_i)^2}{(O_i + M_i)}}$$

Equation 1. GEH Statistic. Where Oi is the observed OD matrices and Mi represents the modelled OD Matrices

Table 2: GEH statistic comparison

OD GEH<5	268401
Total OD Pairs	270400
% GEH<5	99.26

Finally, the last factor to validate the calibration procedure is the modal split from the model. In the original Regensburg model, the mode shares are 9.97% and 90.02% for PT and private modes, respectively, as shown in Table 3. On the other hand, after the calibration of the mixed traffic model, the modal shares are 8.16% and 91.84%, respectively. Thus, the change in modal shares is less than 2%, which shows that the calibration is good. After the model has been successfully calibrated, the logical step is the introduction of bus lanes in the network, which will be described in the next section.

Table 3: Modal split comparison for calibration

	Original Regensburg Model	**Mixed Traffic Calibrated Model**
Trips PT (-)	276,465	234,036
Trips PrT (-)	2´496,287	2´634,459
Share PT (%)	9.971	8.159
Share PrT (%)	90.029	91.841

4.5.2.1.2.2 Introduction of Dedicated Bus Lanes

A simplified methodology has been formulated to represent the inclusion of bus lanes in Regensburg. The methodology is based on modifications to the transport network and the procedure sequence. In the following produced results, the different modifications are described.

4.5.2.1.2.2.1 Network Modifications

The first step to model the dedicated bus lanes is to introduce such infrastructure in the network. In order to simplify this process, a User-Defined Attribute (UDA) is introduced to distinguish the links with dedicated bus lanes. This attribute is defined as “IsSegregated”, which takes the value (0) when there is no segregation of the bus lane and the value (1) when the link has a dedicated bus lane. Initially, all the links in the network are defined as “IsSegregated=0” by default.

The implementation of the bus lane also influences the capacity of the lanes. In the original Regensburg model, lane level capacities are not defined, but rather the capacity is defined only for a complete link (single direction). Therefore, an auxiliary UDA “CapacityPrTPerLane” is created to quantify the capacity of every lane per link. Equation 2 represents the formula used to calculate the value for the attribute.

$$CapacityPrtPerLane_{link\ i} = \frac{TotalCapacityPrT_{link\ i}}{Number\ of\ Lanes_{link\ i}}$$

Equation 2. “CapPrTPerLane” formula for each link

In order to assign the bus lanes, three data must be established by the modeller. These inputs relate to the Line route in which the dedicated bus lanes are to be implemented. The main data that must be known are described in Table 4. Based on that information, the modification of the network can be executed. The process starts with the selection of the relevant PT line routes, using the filter function and then the links which are used by the selected line route. Using the filter functions, the planner can introduce the attributes (Table 4) of the desired bus lanes to be converted to dedicated infrastructure. The result of this filter will isolate the relevant line routes from the remaining line routes. Based on the segregated line routes, the filter function also isolates every link that is used by the desired line routes.

Table 4: Input data for the selection of PuT line

Attribute	Description
Line Name	Name of the public transport line
Name	Integer identifier of the route service desired
DirectionCode	Code of the direction of the line (H) or (R)

With the dedicated bus lanes identified, the attributes of the pertinent links must be modified to reflect the decrease in the capacity for private vehicles. The modification is performed using the multi-edit function, for all links used by the dedicated bus lanes. Equation 3. Modified capacity for private vehicles represents the modified capacity of the relevant links. Furthermore, the “IsSegregated” UDA for the links will be set to the value of 1.

$$CapacityPrT_{link\ i} = CapacityPrTPerLane_i * (Number\ of\ Lanes_i - 1)$$

Equation 3. Modified capacity for private vehicles

4.5.2.1.2.2.2 Procedure Sequence Modifications

The preceding section described the method to identify and integrate dedicated bus lanes into the Regensburg model. However, the dedicated bus lanes and mixed bus lanes behave in the same manner, in terms of travel times for PT, if no adaption is done in the procedure sequence of the VISUM model. Therefore, a procedure adaptation has been implemented, wherein the links having UDA "IsSegregated" value as (0) will be filtered (which are the links with mixed lanes). These links (and the lanes in them) will be updated with the mixed traffic travel times from the traffic assignment model. Conversely, in the dedicated bus lanes, free-flow travel times will be considered for PT vehicles.

4.5.2.1.3 Generation of agents based on path sequences

One of the advantages of the VISEM model is the possibility to model the tours of every agent discretely. This benefit can be accessed by using the "Calculate Path Sequence Sets" procedure in the combined trip distribution and mode choice module in VISUM. Since the Regensburg model is not originally intended for this purpose (i.e., generation of path sequences), some assumptions and slight modifications are made. In the subsequent sections, pertinent concepts, adjustments and procedures used to extract the individual trip data will be presented.

4.5.2.1.3.1 Basic concepts

As mentioned beforehand, the VISEM model allows exporting the path sequences to analyse trips. Therefore, it is important to introduce what is a path set and which are the elements that it includes. In an activity-based model like VISEM, a path sequence represents each tour of an agent (PTV Group, 2020). Moreover, each path sequence consists of a series of path sequence items. This element represents each segment of a tour and indicates the origin, destination and the mode used. Another relevant term is the Path Sequence Set. This term corresponds to a structure, which seeks to group all path sequences, based on the information of the agent that executes the tour. In the case of the Regensburg VISEM model, the path sequence sets are defined by the activity chain and the different person groups. A total of 843 path sequence sets are found in the model. Figure 20 illustrates the hierarchy of the different terms presented in this section.

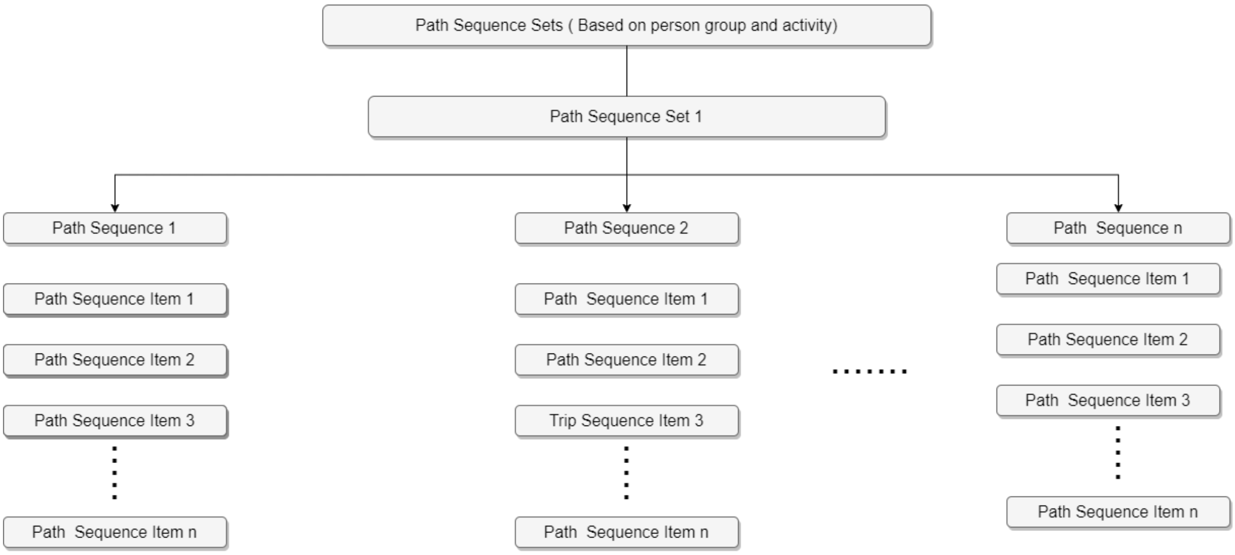


Figure 20. The general structure of Path Sequences Sets

4.5.2.1.3.2 Calculation of Path Sequences

For the calculation of path sequences, the time interval of the demand time series should be same for all the activity pairs of a person group (i.e., time series for the same person group must either be constant or have the same time interval). After inspecting the demand time series, it has been determined that the activity pair Work-Home (AW) is in a different format from the other activity pairs. The activity pair AW is defined in a time frame from 6:00 -19:00 with no hourly distribution. In contrast, the time series of the remaining activity pairs are defined on an hourly basis. In order to overcome the discrepancy, an artificial time series has been created for AW activity pair, using the Mobilität in Deutschland (MiD 2017) data.

4.5.2.1.3.3 Extraction of the Trips

To extract the trip data required from the model, a methodology using the Python COM in VISUM is implemented. The implementation begins by opening the VISUM file, in which the trip sequences are constructed according to the time series. The first step of the code is to create the OD pair list from VISUM, with the parameters of origins, destinations, distances, and travel times, according to the different modes. Afterwards, the code will run through the 843 path sequence sets present in the model and save all the trips to a CSV file. The final step is to add the WGS 84 coordinates for origins and destinations. To extract the coordinates, the zone centroids are exported and projected in ArcGIS.

4.5.2.2 Modelling framework for shared mobility services

The modified VISUM model will be used as a basis for the development of a modelling framework for the shared mobility services. The existing car-sharing service in the city of Regensburg is a small system (< 10 vehicles) and it has been planned to gradually expand the service. Currently, the planned expansion is not large-scale and therefore, it can be considered that this system will not have a substantial impact on the existing travel times in the city. Similarly, the one-way bike-sharing service can also be considered to not (substantially) impact the existing travel times in the next 4-5 years, as the system is yet to commence. Therefore, historical travel times from the existing VISUM model can be used for the modelling of the shared services. Due to this assumption, an iterative interaction with the traffic assignment step is not required, which simplifies the overall modelling schema presented in D4.1.

Given the possibility to discretely evaluate tours for every agent in the existing model (because of the VISEM procedure), the generation of synthetic population through the open-source tool 'PopGen' can be omitted. However, since the agents from the VISEM procedure will not have any socio-demographic characteristics, individual and household specific variables have to be added to the agents through an external procedure. This will be achieved through the statistical matching procedures, which is part of synthetic population generation module. Following the integration of socio-demographic variables to the agents, the disaggregate mode choice model will be run to generate demand for the bike-sharing system. For the car-sharing system, the data-driven car-sharing demand model (developed as part of the induced demand module) will be used. Upon executing the above two models, the demand for the shared mobility services is fed into the fleet management module, to assign sharing vehicles and simulate the service requests.

If any of the service requests are rejected, due to vehicle availability or walking constraints (long distance to the shared vehicle station), the disaggregate mode choice model is re-run for those requests, to assign a new alternative mode, until no rejection is observed. Subsequently, the static emission model is run to obtain emissions and finally, required KPIs are calculated based on the result from the individual modules.

4.5.3 Models´ implementation and calibration

Statistical matching procedures are generic methods. Therefore, no calibration procedure is implemented. Regarding mode choice, the demand for bike-sharing service will be based on the disaggregate mode choice model described in D4.1. Since the service is yet to start operation in Regensburg, no relevant data is available for calibration of the mode choice model. Hence, sensitivity analysis will be carried out for the synthetic population and manual adjustments of the coefficients are made where required. In case of car-sharing, the data-driven model has been estimated directly using the data from the Regensburg city and hence, no calibration is required. Similar is the case for the aggregate car-ownership model. Concerning fleet management module, similar to statistical matching procedures, they are generic methods and hence, no special calibration is done. The station locations for the shared services will be pre-defined. The fleet size will either be pre-defined or based on Level 1. Network from PTV is imported to Aimsun Ride (within which the shared vehicles will be simulated). Existence of any errors will be identified and corrected, to ensure compatibility and possibility of data transfer between the two different platforms. With regards to emission model, the static emission model has been designed to accommodate country-specific emission factors and German specific emission factors will be used for the Regensburg case study, without any further calibration.

A summary of different new developments, which are implemented in Regensburg case study, is presented in Table 5.

Table 5: Summary of the new implementations

Step	Implementation
Inclusion of APM	Addition of the mode as part of the existing PT system
Inclusion of dedicated lanes	Load PT vehicles into the road network and reflect the implementation of dedicated lanes through change in link capacities
Synthetic population	Agents based on path sequence sets, and use of statistical matching procedures for adding socio-demographic details
Demand for bike-sharing	Application of the disaggregated mode choice model, after carrying out sensitivity analysis
Demand for car-sharing	Direct application of the induced demand model for roundtrip station-based car-sharing
Fleet management	Use of common procedures related to the fleet management module, as described in D5.1. The station locations are pre-defined. The fleet size will either be pre-defined or based on Level 1. For bike-sharing, vehicle rebalancing will be introduced.
Emission	Direct application of the static emission model, based on the Regensburg fleet data.

4.6 Leuven Case Study

4.6.1 Introduction

The city of Leuven is located central in Flanders, Belgium, about 25 km eastward of Brussels. It is a relatively small city with just above 100 000 inhabitants. Next to these people domiciled in Leuven, there is also a large group of about 35 000 students that effectively live in Leuven during the week but are officially living elsewhere. These students are mainly the result of Belgium's largest university, KU Leuven, having its main campus in Leuven. The university also results in a rather large share of inhabitants of foreign nationality (about 18%) and a generally high level of education. (Deliverable 2.2 and (Stad Leuven, 2018)).

In terms of shared mobility services, Leuven has a bikesharing system and a carsharing system. The bikesharing system is station-based and of round-trip type. It only has stations near the train stations. The carsharing system is also of round-trip type. It is operated by several different companies which have stations all around the city.

Some other types of shared mobility services, such as non-station-based ones, are probably not feasible in Leuven due to its rather small size, both in terms of area and population.

The main MOMENTUM-developed model components that will be used in the Leuven cases studies are the disaggregate car ownership module, the induced demand module, and the emission module (all described in D4.1). For the main rationales behind these modules and how they fit within the shared mobility modelling framework, we also refer the reader to D4.1.

Here, we will first describe the local model workflow for Leuven (subsection 4.6.2). In order to understand the possibilities and limitations of the local workflow, first a comprehensive overview of the available local data and its pre-processing is given. Next, all important model components (and their calibration) comprising the overall Leuven model are described. The focus in subsection 4.6.2 is on the non-MOMENTUM-specific modules, as the MOMENTUM-specific ones are described later on in subsection 4.6.3. Finally, we show how the different submodules link together when evaluating scenarios.

In subsection 4.6.3, we provide details on the calibration and implementation of the MOMENTUM-specific modules. Referring to the overall Leuven model, we point out how these models fit within the larger picture explain in depth how the calibration is performed.

4.6.2 Local Workflow

4.6.2.1 Overview of available data

In the Leuven case study, a variety of data sources is used. Some of this data is publicly available, while other parts are provided by the government or private companies. In this subsection, a detailed overview of the used data is provided.

The traffic model for Leuven is in large based on the Flemish government's regional traffic model ("regionaal verkeersmodel v4.2.1", or for short ***RVM***) (Departement Mobiliteit en Openbare Werken, Vlaanderen, 2021). This is an agent-, tour- and activity-based multimodal traffic model, which is, however, too coarse grained to be used directly as a city traffic model. Parts of this traffic model are used to build a more refined city model. We detail these parts below.

It is first important to give an overview of the **zoning system** that is being used. In the pre-defined study area in and around Leuven (Figure 21), a rather fine zoning system—closely related to statistical sectors—is used. These zones that are physically located within the study area are called **internal zones**. Traffic that passes through this study area but has its origin or destination on the exterior of it, is assumed to enter or exit the study area by one of the major roads. For each of these major roads, a virtual zone is created that acts as the origin or destination for this traffic and they are directly attached to the particular major road. These virtual zones are called **external zones** since they accommodate external traffic entering the local road network. Including this traffic is important since it traverses the study area and loads the local road network. In terms of origin-destination (OD) pairs, we call an **OD** pair **internal** if both the origin and destination zones are internal zones. If either or both origin and destination zones are external zones, the OD pair is called **external**.

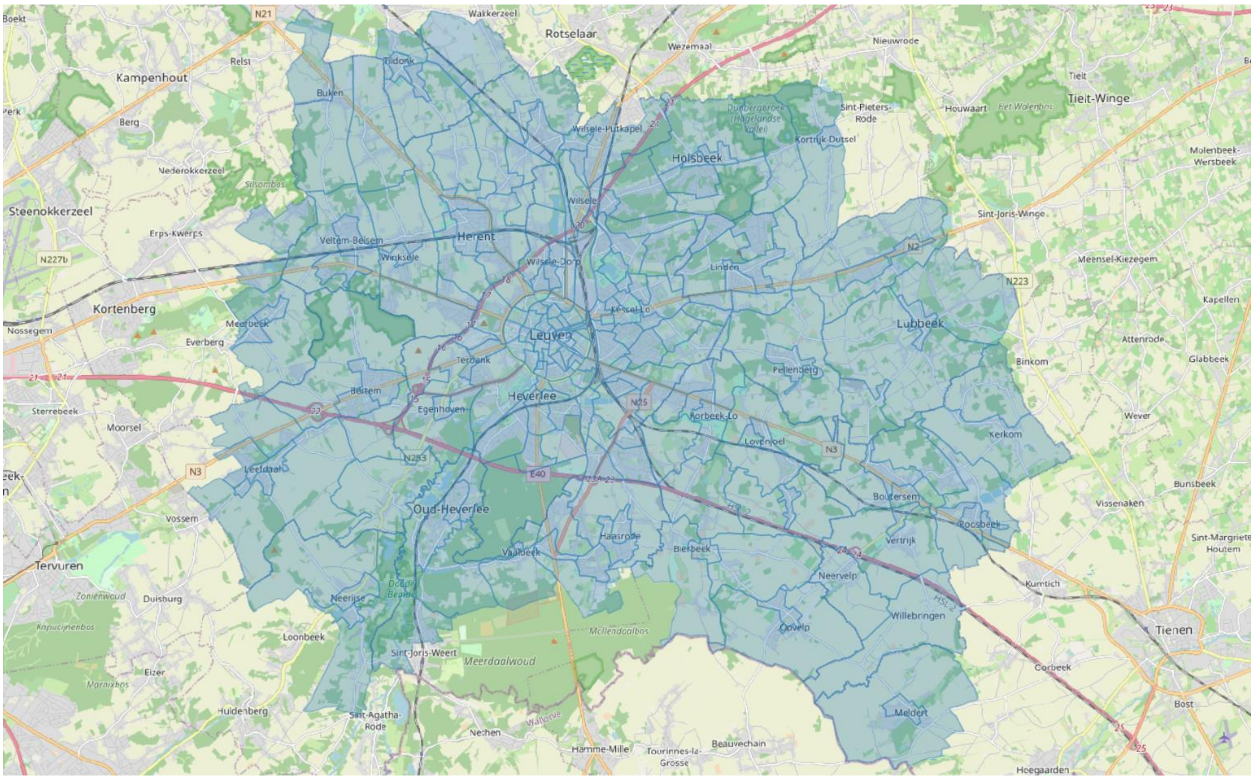


Figure 21 Zoning system that is used in and around Leuven.

OD demand matrices are readily available from the RVM for trucks and cars, on an hourly basis for the hours 7, 8, 16 and 17. For trucks, we use the full (both internal and external OD elements) demand matrix. This provides a full overview of the truck demand, which is kept constant in our model. For cars, we only use the external OD pairs of the demand matrix. The combination of this truck and car demand will be referred to as '**external and truck OD demand**'. The non-truck demand for internal OD pairs will be derived from the trips, which are discussed next.

The RVM is a tour-based model. Each tour is defined as a series of two or more trips. For each of those trips, the origin, destination, and departure hour are given. Each tour starts and ends at the living place of the agent that makes the tour. Additionally, each tour contains information on the agent that makes it, what the main destination of the tour is, and the mode choice probabilities. All tours with a stop in one of the internal zones are available. These tours can be split into the trips that compose them. We only keep the **internal trips**, i.e., trips that have both for their origin and destination an internal zone. For each of these trips, we store which agent makes the trip, at what hour, and the **mode choice probabilities** (car, public transport (PT), bike, and foot).

Because the RVM is an agent-based model, we have a **full synthetic population, including agents and the households** (HH) they belong to. The synthetic population (SP) consists of all agents that make an internal trip and their households. The attributes in the synthetic population are:

attribute	description
agent_id	unique id for the agent
hh_id	unique id of the household to which the agent belongs to
zone	zone of the living place of the agent
gender	gender of the agent
age	age of the agent
occupation	occupation/status of the agent (active/working, retired, student, other)
diploma	highest diploma of the agent (no, secondary, higher)
ebike_bln	Boolean indicating whether the agent has an E-bike
company_car_bln	Boolean indicating whether the agent has a car provided by its company
car_at_disposal_bln	Boolean indicating whether the agent can make use of a car
hh_nbr_cars	number of cars in the household
hh_type	type of household (for example, single with children etc.)
hh_income_category	net income category of the household in euro
hh_nbr_actives	number of active members in the household
hh_size	number of members in the household

An important remark is that there is a special household type, which we call the *displaced students*. This type is specifically important to Leuven and more generally Belgium. In Belgium, university and university college students typically go live in the city of their education institution during the week. However, they return home during the weekends and keep their domicile at their parents' home all the time. For the RVM modelling purposes, however, they are displaced to the city of their education institution, living separately in a displaced student household type. Nevertheless, they keep some of their original household's attributes (such as number of cars in the household and salary) while their socio-demographic situation is often different in reality. This is a fact that one should be careful of in the analysis of the results since Leuven is a major student city in Flanders.

The **city monitor survey**, conducted in 2017 (Agentschap Binnenlands Bestuur, 2017) contains both socio-demographic information of the respondents and their households, as well as their mobility preferences and attitudes. The available attributes of the survey that we use are:

attribute	description
city part	part of the city where the respondent lives (8 city parts are distinguished, see Figure 22)
gender	gender of the respondent
age_cat	age category of the respondent (8 categories are distinguished)
hh_type	type of household of the respondent (6 types are distinguished)
hh_size	size of the respondent's household
education_isced	ISCED classification of the respondent's highest diploma
labour_status	labour status of the respondent (6 categories)
income_cat	net household income of the respondent's household (11 categories)
Belgian_bln	Boolean indicating whether the respondent is Belgian
hh_nbr_cars	number of cars in the household of the respondent
hh_ebikes	number of E-bikes in the respondent's household
hh_public_transport_passes_bln	Boolean indicating whether any member of the respondent's household has a public transport pass
hh_cargo_bikes_bln	Boolean indicating whether any cargo bikes are present in the respondent's household

hh_carsharing_subscription	Boolean indicating whether any carsharing subscriptions are present in the household of the respondent
carsharing_willingness	Boolean indicating whether the respondent is willing to use carsharing services
commute_distance_km	commute distance in km for the respondent
response_weight	weight for the response, correcting for city part weight and nonresponse weight

Notice that not the entire study area is covered by the city parts of the city monitor survey (compare Figure 21 and Figure 22). This means that some part of the synthetic population lives in zones that are covered by the survey, while others live outside that area. To ease further discussions, we introduce the concept of **surveyed and non-surveyed synthetic population/agents/households**. By a surveyed agent, we mean an agent that lives in one of the zones that was included in the city monitor survey, and similarly for the surveyed synthetic population and households. Non-surveyed denotes the opposite, of course. For the surveyed synthetic population, it is straightforward to make a mapping between the RVM zones and the survey's city parts.

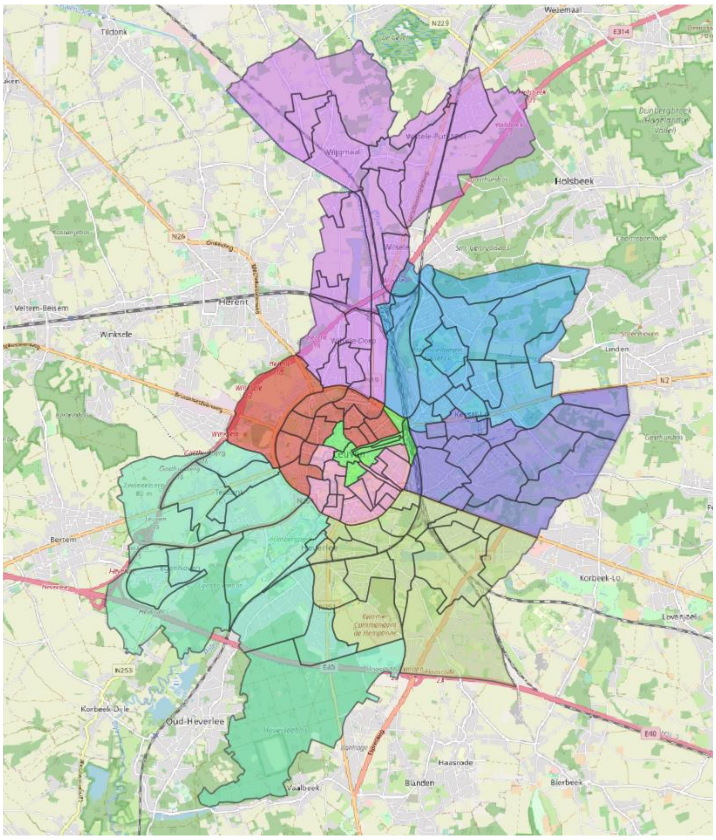


Figure 22 Coloured mapping of the city monitor's city parts, which are equivalent to the car sharing city districts.

For the city of Leuven, detailed **car sharing supply** data is available for the year 2019. This data encompasses the number of available station-based shared cars in each city district. These city districts are the same as those in the city monitor survey (Figure 22). On the other hand, spatially aggregated data on the car sharing supply that was available for the year 2017 was used to rescale the 2019 data to reasonable 2017 data. This is necessary because the developed car sharing models are calibrated based on the city-monitor survey data, which was conducted in 2017. A suitable car sharing supply can thus be assigned each respondent of the city monitor survey as well as to each member of the surveyed synthetic population through the mapping that exists between the city districts and the RVM zones.

The **road network** for the city of Leuven is obtained through OpenStreetMap (OSM) (contributors OpenStreetMap, 2020). The area for which roads are loaded is in good proximity identical to the study area, shown in Figure 21. Several corrections to better represent reality are applied. These include the correction maximum driving speeds, one-way routes, and the number of lanes.

The area for which the road network is loaded, is divided into zones that match with the RVM zones, described above. For each zone, at least one origin and destination connector is chosen, which serves to inject traffic into the network at the origins and extract it again at the destinations. Moreover, each of the links and nodes of the network gets assigned a zone number, which corresponds with the zone in which they are located.

In terms of the **public transport** (PT network), the model is based on the General Transit Feed Specification (GTFS) (MobilityData, 2021) of the local bus service provider De Lijn and the passenger rail transport provider NMBS. The GTFS data is pre-processed to identify matching transfer stops. A time-expanded graph method (Schulz, 2000) is used to get schedule-based travel times between all possible pairs of stops. These are then augmented by the travel time by foot towards and from each stop. This information is combined as to calculate the shortest travel time between all zones. That travel time is used in the Leuven model to represent the travel time by public transport.

Two main sources of **traffic counts** are available, which will be used for calibration:

- Verkeersindicatoren (Vlaams Verkeerscentrum, Vlaamse Overheid, 2020): these are continuous traffic counts on the on-and off-ramps, and traffic interchanges of the Flemish motorway system. These double counting loop-based counts can distinguish car and truck traffic.
- Telraam (Telraam, 2020): These are automated traffic counts on non-motorway streets. This camera-based counting method can distinguish different modes of transport, such as trucks, cars, and bikes.

Finally, the **cost-elasticity of demand** is required for calibration of the induced demand model. Based on a thorough literature review, the short-term direct time-cost elasticity for car travel demand is set to $\eta_{\mathrm{car}} = -0.6$ (de Jong, 2001).

4.6.2.2 Pre-processing of data

Later, models related to car sharing will be calibrated based on the mobility survey and applied to the synthetic population, such that the effects on the overall transport system can be estimated. Unfortunately, not all RVM and survey attributes match exactly right away, making it difficult to calibrate the models on one dataset and apply them to the other. To resolve this inconvenience, we (i) distil attributes that are compatible between the synthetic populations and the survey and (ii) extend the synthetic population with additional survey attributes.

Some attributes were absent in our synthetic population, while being potentially important indicators for our carsharing models. These attributes had to be added to the synthetic population, based on the information present in the mobility survey. To add these **extended attributes** to the synthetic population, we trained a state-of-the-art machine-learning model on the survey data using the Python library Scikit-Learn (Pedregosa & et al., 2011). Specifically, a random forests (RF) regression model is developed to estimate the conditional probability of the unknown attributes with respect to a set of predefined common attributes. RF are ensembles of decision trees, which expand themselves using the explanatory variables (common attributes between survey and synthetic population) to obtain leaves as simple as possible for the target variables (attributes that are absent in the synthetic population, but present in de survey). RF are chosen instead of single decision trees as they reduce variance, by averaging weak decision trees (trees that are not fully expanded), and hence, reduce overfitting and improve generalization. In this way, the target variables *is_Belgian_bln, has_cargo_bike_in_hh_bln, has_carsharing_subscription_in_hh_bln, has_pt_pass_in_hh_bln* and *is_unwilling_to_use_carsharing_bln* were added to the synthetic population based on the explanatory variables *living_place_city_part, age_category, education_level, gender, household_type, household_size, occupation, income_category, number_of_cars_in_household, E-bikes_in_household*.

Finally, some of our models require to know the agent's **commute trip distance**. Given the fact that for each tour is indicated what the main destination and agent's living place is, the distance between those can be calculated. The maximum of those main destinations' distances is for each agent stored as a proxy for its commute trip distance.

4.6.2.3 Model components

In this section, we explain some of the building blocks of the Leuven case-study. These building blocks are important in understanding the entire model dynamics and structure. Those building blocks that are specifically developed for the MOMENTUM project (see D4.1) are detailed further in section 4.6.3. The inputs of all model components described here, are either the (pre-processed) available data, or the outputs of other model components.

4.6.2.3.1 OD demand construction

We construct aggregated OD demand matrices from our internal trips with corresponding mode shares and the external and truck OD demand matrices. We distinguish the internal and external OD demand matrices, where the former contains only the demand for internal OD pairs. The latter contains all remaining demand. The model works with separate OD demand matrices for each model hour. In this section, we describe how the OD demand matrix is built for one of those hours.

The external OD demand matrix consist of all demand from, towards and between external zones. This matrix can be directly obtained from the external and truck OD demand matrices for the hours 7, 8, 16 and 17 and for the modes truck and car. No data is available for other hours or modes. Since trucks and cars are an important model component, the model is only applicable for those four morning and evening peak hours. No external OD demand information is available for the other modes that are considered (bike, foot and pt.). As a result, the external demand for those modes is set to zero. However, this is not a problem as these modes are uncongested anyway.

The internal OD demand matrix for the trucks is constructed directly from the external and truck OD demand matrix as well. For the other modes, it is constructed from the internal trips in combination with their mode shares.

Specifically, the trips are grouped by their hour, origin, and destination. For each of those combinations, all trip mode shares are aggregated to construct the mode-specific OD demand matrices.

Finally, the internal and external OD matrices are combined to create the full OD demand matrix. The entire procedure is schematically shown in Figure 23.

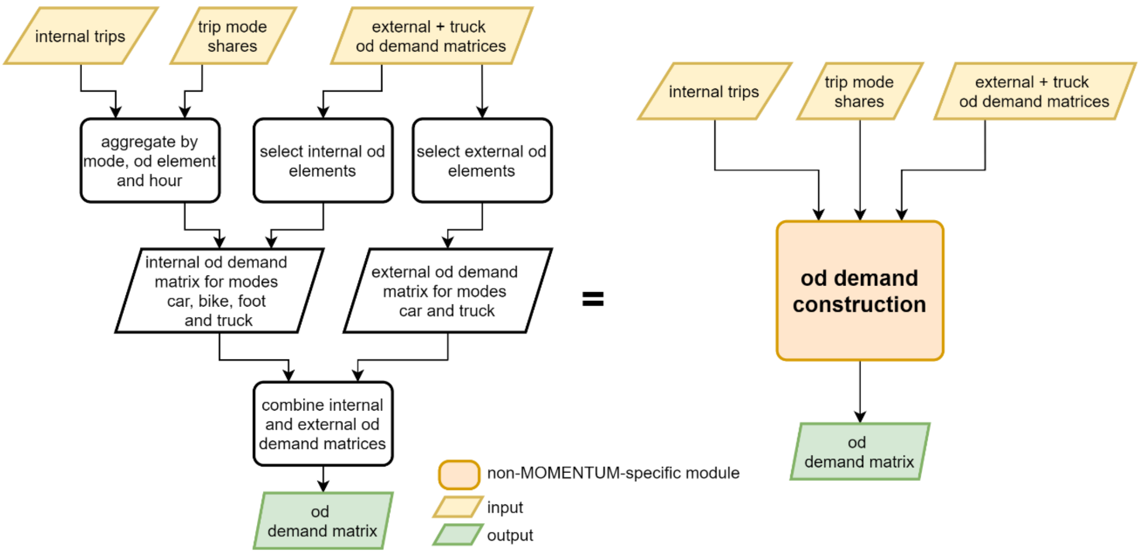


Figure 23 OD demand construction model component. The left-hand side shows the detailed flow chart, while the right-hand side shows the equivalent model component.

4.6.2.3.2 Assignment

The static assignment module assigns the full OD demand matrix for the modes truck, car, bike, and foot onto the road network (see schematic in Figure 24). The public transport mode does not need to be assigned separately, as the travel times are readily available from the expanded graph method, as described in section 4.6.2.1.

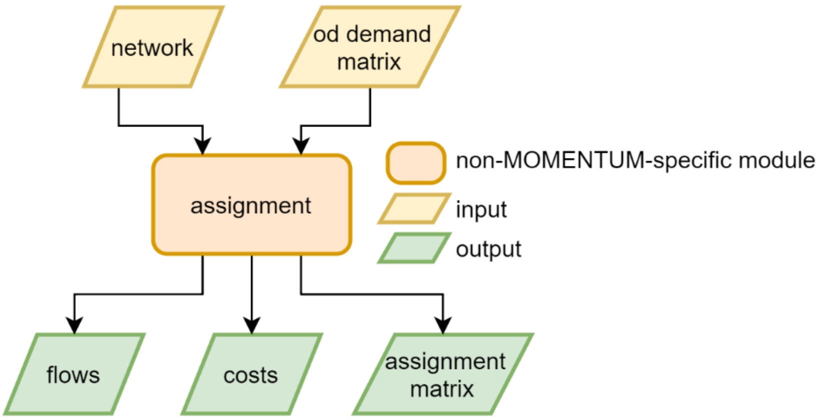


Figure 24 Schematic flow diagram of assignment module.

The module allows to choose either the classical assignment with connectors, or the innovative assignment without connectors that was developed in D4.1. In both cases, the outputs that can be retrieved from this module are:

- Link flows: Intensity on each link for the given mode of transport, expressed in passenger car units (PCU).
- Costs: Time it takes to traverse each link. These can be directly used to calculate total trip or OD trip. costs. As such, the trip and OD costs will also be considered as an output of this module.
- Assignment matrix: The link flows, but now disaggregated for the different OD pairs.

The modes bike and foot are being assigned uncongested—that is, with fixed travel speeds that are unaffected by link flow intensities—since congestion is typically negligible for these modes. The modes “truck” and “car”, get assigned with congestion taken into account.

4.6.2.3.3 Disaggregated mode choice model

As described in section 4.6.2.1, we have a mode choice distribution available for each internal trip made by our synthetic population. To evaluate how changes in the synthetic population’s attributes or road network affect the mode choice, it is indispensable to have a disaggregate mode choice model that is Leuven-specific. To calibrate such a model, we rely heavily on the gained insights from the disaggregated mode choice model calibrated for Madrid in D4.1 and on the wealth of information available in our synthetic population combined with the trips and mode choices from the RVM.

The mode choice model is of multinomial logit type and was iteratively calibrated using PandasBiogeme (Bierlaire, 2020) to only retain the most relevant parameters. It is important to use the original RVM model parameters to perform the calibration: RVM trip mode shares, RVM synthetic population attribute values and the original, unaltered network. The final utility specifications, which was optimized in terms of maximum loglikelihood, t-statistic of the parameters and adjusted ρ^2-values, is (c=car, pt=public transport, b=bike, f=foot):

$$U_c = C + \beta_{\text{travel time}} \cdot x_{\text{car travel time}} + \beta_{\text{company car}} \cdot x_{\text{bln has company car}} + \beta_{\text{student}} \cdot x_{\text{bln occupation is student}} + \beta_{\text{multiple cars}} \cdot x_{\text{bln has multiple cars in hh}} + \beta_{\text{displaced household}} \cdot x_{\text{bln has hh type 0}}$$

$$U_{\text{pt}} = C + \beta_{\text{travel time}} \cdot x_{\text{pt travel time}} + \beta_{\text{student}} \cdot x_{\text{bln occupation is student}} + \beta_{\text{retired}} \cdot x_{\text{bln occupation is retired}} + \beta_{\text{active}} \cdot x_{\text{bln occupation is active}}$$

$$U_b = C + (\beta_{\text{travel time, E}} \cdot x_{\text{bln has E-bike}} + \beta_{\text{travel time, non-E}} \cdot x_{\text{bln has no E-bike}}) \cdot x_{\text{bike travel time}} + \beta_{\text{retired}} \cdot x_{\text{bln occupation is retired}} + \beta_{\text{active}} \cdot x_{\text{bln occupation is active}}$$

$$U_{\text{foot}} = C + \beta_{\text{travel time}} \cdot x_{\text{foot travel time}} + \beta_{\text{retired}} \cdot x_{\text{bln occupation is retired}}$$

The values for the calibrated intercepts C and parameters β, together with their t-statistics and interpretation are summarized in Table 6.

Table 6: Calibrated parameters of the disaggregated mode choice model. The calibration is based on 985440 samples. The final log likelihood is -931017.6 and the adjusted ρ^2 0.307.

calibration parameter	mode	value	t-statistic	interpretation
intercept C	car	0	NA (fixed value)	
	pt	-2.75	-152	
	bike	-0.754	-95.7	
	foot	-0.83	-108	
$\beta_{travel\ time}$ (units: $minutes^{-1}$)	car	-0.0696	-68.3	Larger travel times lead to lower utilities. Travel time by public transport has a better perception, because people can do other things while traveling. Note, however, that pt starts with a large initial cost due to its intercept.
	pt	-0.00963	-51.5	
	E-bike	-0.0599	-68.4	
	non-E-bike	-0.0749	-165	
	foot	-0.0432	-224	
$\beta_{company\ car}$	car	0.0841	12.2	People with a company car are more likely to take the car.
$\beta_{student}$	car	-1.37	-169	Students typically do not have a driving license or car. They must use the public transport as an alternative.
	pt	1.08	61.1	
$\beta_{multiple\ cars}$	car	0.706	133	When a household has multiple cars, they use them more.

$\beta_{displaced\ household}$	car	-1.76	-151	Correction for the displaced student household, that still has some of the original attributes, but typically do not own a car.
$\beta_{retired}$	pt	-0.716	-29.1	Retired people have a relative preference for the slow foot mode or to use their car.
	bike	-0.492	-41	
	foot	0.161	13.2	
β_{active}	pt	0.344	18.9	Active people often commute by public transport. Biking is also a popular means to reach the destination.
	bike	0.273	37.8	

In addition to the above model specification, it should be noted that the car mode choice was only made available to people that have at least one car in their household.

The mode choice is to be applied to all internal trips, which can be made by any agent of the synthetic population. The survey-extended synthetic population attributes, such as having a public transport pass in the household, were only added to the surveyed synthetic population, as described in section 4.6.2.2. Consequentially, they could not be used in the mode choice utility specifications.

The utility specification above does not contain any origin-or destination-specific attributes, except for the OD travel time. In order to better capture any origin and destination specificities, an additional mode utility offset constant is estimated on a per-od basis in a post-processing step to the calibration. These constants are estimated such that the aggregated OD demand matrices obtained after applying the mode choice model are in close agreement with the original OD demand matrices. The entire calibration process is schematically shown in Figure 25.

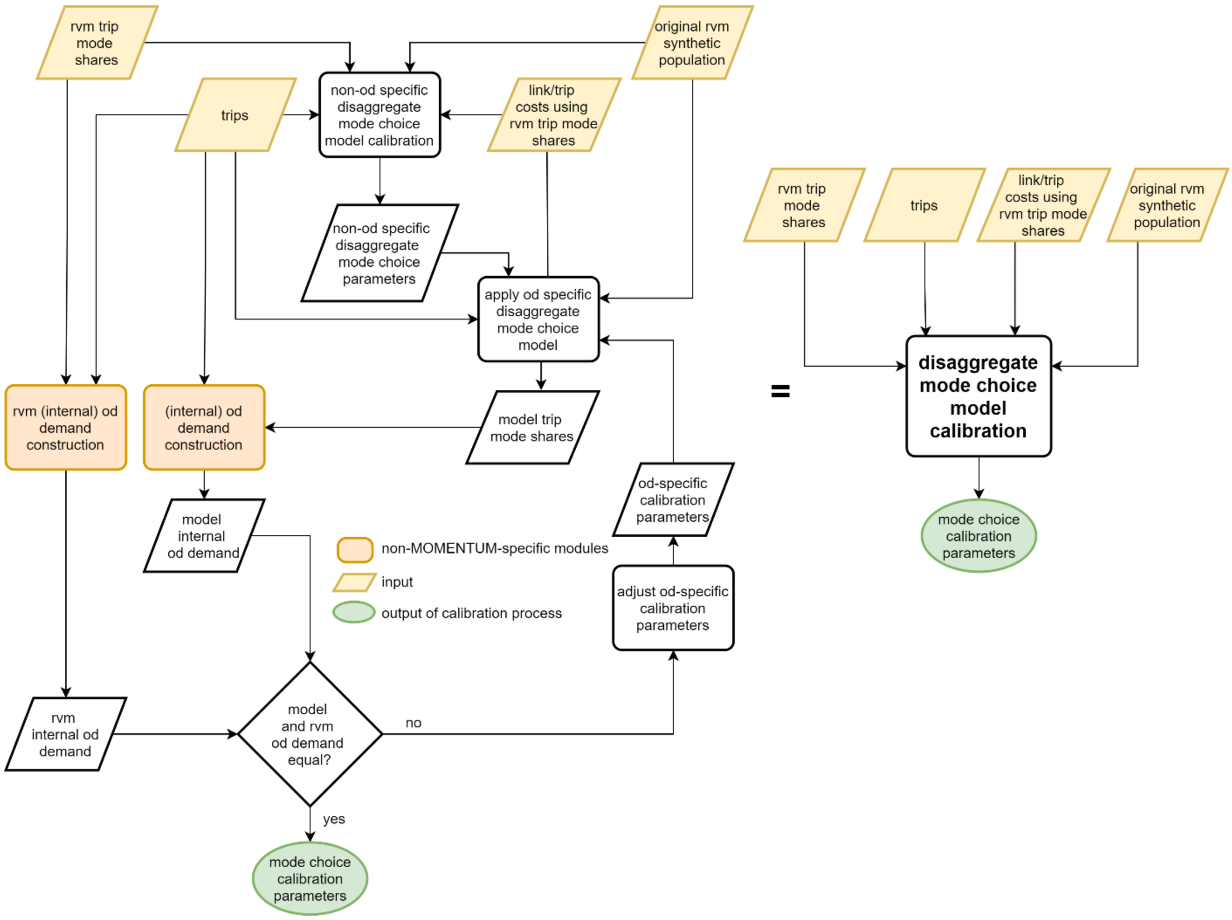


Figure 25 Detailed mode choice model calibration scheme and the equivalent with only inputs and outputs shown. The calibration must be performed using the original RVM synthetic population attributes, the original RVM mode choice and the link/trip costs that are calculated using the original (base) road network and RVM mode choice.

The final mode choice model (Figure 26) is able to translate changes in the population or road network into adapted trip mode shares, which after aggregation lead to modified mode-specific OD demand matrices. Moreover, it manages to closely reproduce the original mode-specific OD demand matrices. This means that having the calibrated mode choice model available, we do not need to keep the original mode shares around. The inputs to apply the calibrated mode choice model are the synthetic population characteristics (which can be altered in a scenario), the internal trips and the associated travel times (which can be altered through people's mode choice and the road network characteristics).

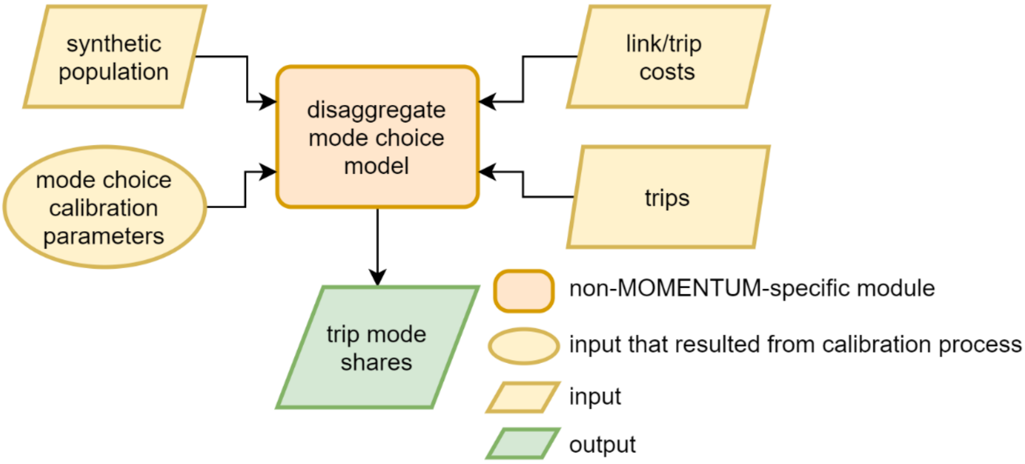


Figure 26 Schematic of inputs and outputs of the disaggregate mode choice model.

4.6.2.3.4 OD demand calibration

The calibration module serves to adjust the values in the OD demand matrices in such a way that the flows obtained through assignment agree with the observed traffic. This demand calibration works by assigning aggregated demand matrices repeatedly onto the road network. In each iteration, the demand is slightly altered until the assigned flows match sufficiently well with the observed traffic. Since only reliable traffic counts for trucks, cars and bikes are available, only these mode's OD demands can be calibrated. Notice that the OD demand calibration works at the aggregated OD matrix level, and not at the disaggregated trip level.

The above procedure—applied to an OD demand matrix and road network that is representative for the moment at which the traffic counts were available—results in a calibrated OD demand matrix for a base scenario. When evaluating a new (policy) scenario, the OD demand matrices obtained by aggregating new scenario mode choices are still uncalibrated. To accommodate the calibration of new scenarios, we calculate calibration factors as the ratio of the calibrated base scenario's OD demand and an uncalibrated base scenario's OD demand (calculated using the most accurately available travel times). Applying those calibration factors to the new scenario's OD demand matrices results in their calibration.

Since the procedure to determine the calibration factors requires the disaggregate mode choice model (to determine accurate base scenario travel times), it can only be applied after the disaggregate mode choice calibration. The entire procedure is schematically depicted in Figure 27.

Making use of the calculated demand calibration factors, any uncalibrated OD demand matrix can now straightforwardly be calibrated by multiplying each mode's OD demand with the corresponding calibration factor. For completeness, the inputs and outputs of this process are shown in Figure 28.

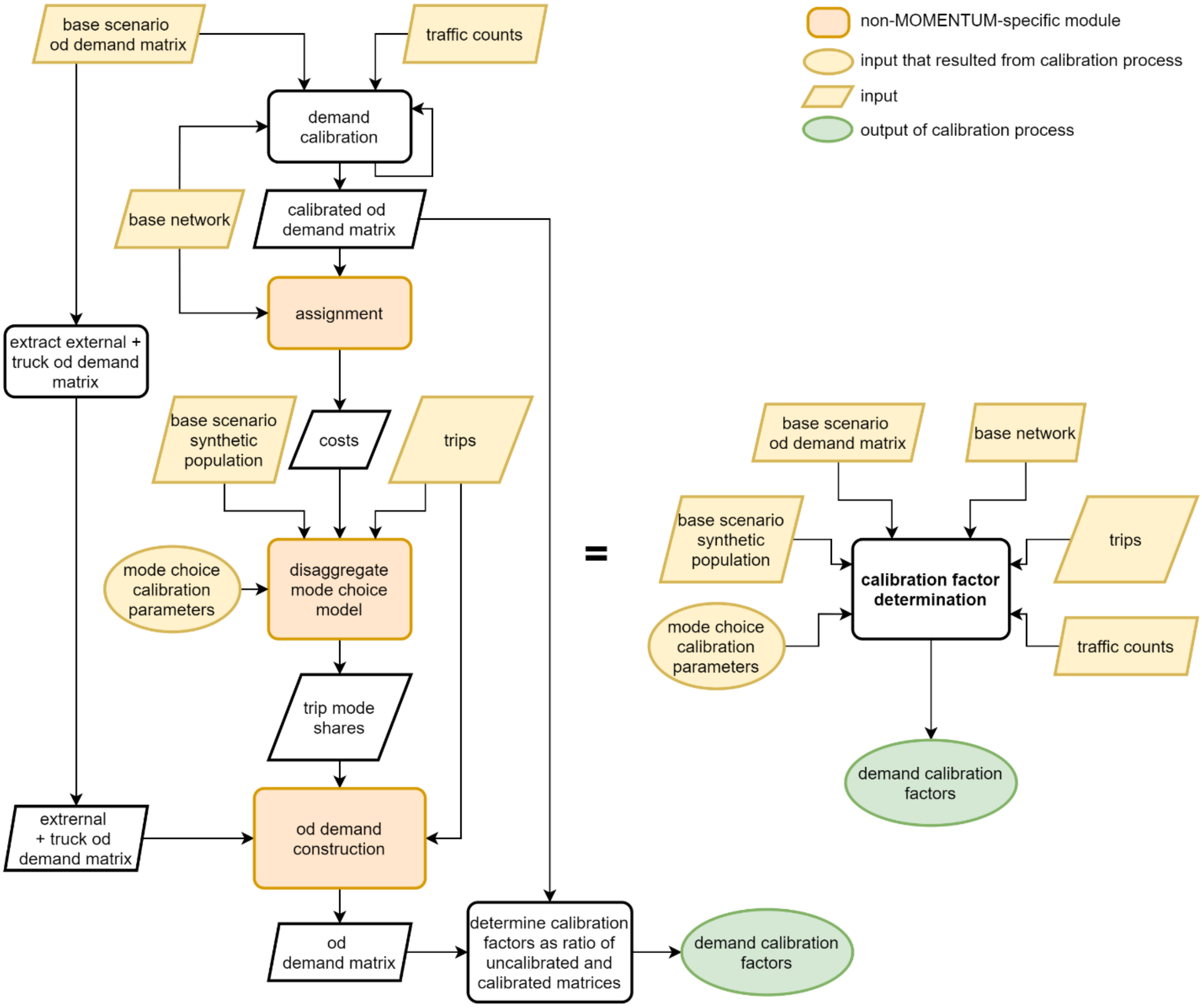


Figure 27 Process to determine calibration factors. On the right, a simplified diagram with only the required inputs and output is shown.

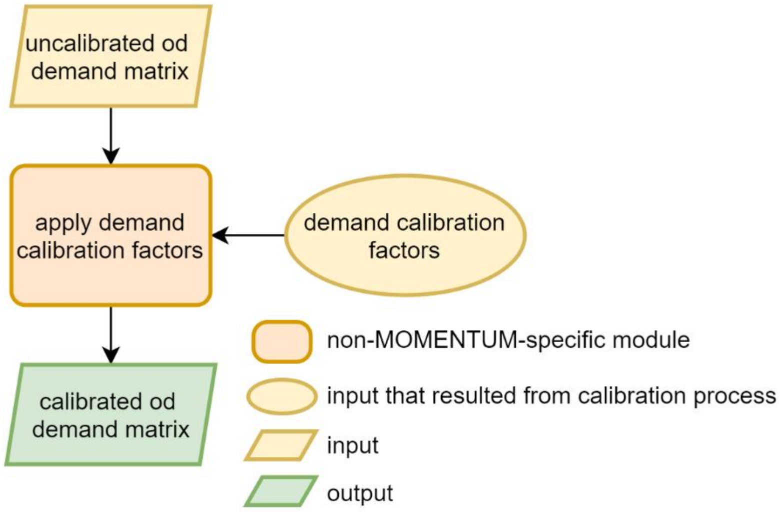


Figure 28 Applying the calibration factors to get a calibrated od demand matrix.

4.6.2.3.5 MOMENTUM-specific model components

The MOMENTUM-specific model components that are in focus in the Leuven case study are the car ownership model, the emission model and the induced demand model. These models were described in full detail in D4.1. Their implementation and calibration will be laid out exhaustively in section 4.6.3. Here, we merely give a short description of their inputs and outputs, such that they can be fitted into the complete Leuven model workflow that is described in subsection 4.6.2.4.

The **car ownership model** calculates probabilities for having a certain number of cars in a household. In doing so, it depends on the extended synthetic population characteristics (meaning it can only be applied to the surveyed synthetic population) and the car sharing supply. The latter allows to evaluate effects of changes in car sharing supply. During the tests of this model, it was found useful to implement a post-processing extension: a car sharing subscription model. This model estimates the probability of having a car sharing subscription at household level, using again extended synthetic population characteristics and the car sharing supply in combination with the car ownership model-calculated car ownership. Having this additional post-processing model allows for a more detailed analysis of the car ownership model results. The overall process is shown in Figure 29.

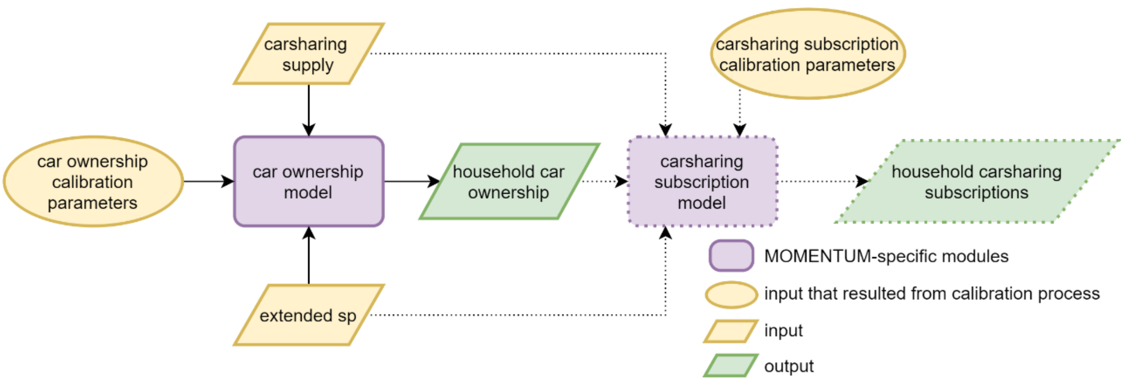


Figure 29 Schematic representation of inputs and outputs of the car ownership model, and optional post-processing car sharing subscription model.

The **emission model** calculates the emissions on a per-link basis. As such, it allows to evaluate the influence of different policies on emissions, with a great level of detail. The emission model is pre-calibrated to account for the types of cars in an EU country on yearly basis. Furthermore, the emission model accounts for the traffic speeds and intensities. As such, the inputs of the emission model are the car flow intensities and car travel speeds at link-level and the road network containing at least the link lengths. The overall process is shown in Figure 30.

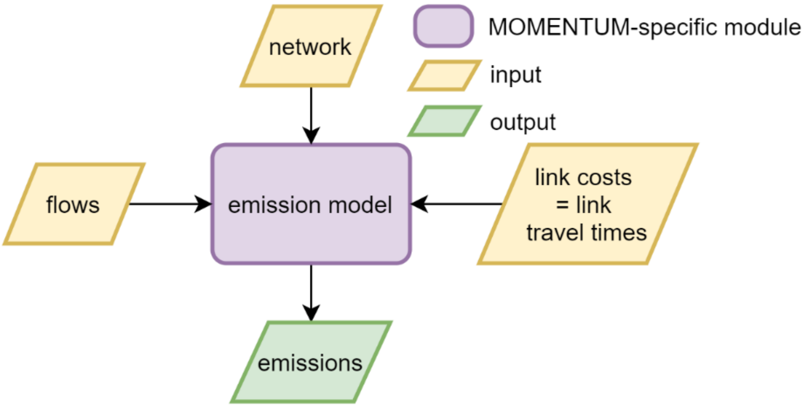


Figure 30 Schematic representation of the inputs and outputs of the emission model.

Changes in mode shares for internal OD demand elements are already accommodated through the disaggregated mode choice model. However, when modal splits change drastically because of a large shift in one of the input parameters, such as travel time, it is expected that also the total OD demand will change. This can be accounted for using the **induced demand model**. Moreover, while before the car OD demand for external OD pairs remained constant, the effects of travel time changes on these external OD elements can also be accounted for through the induced demand model. After calibration of the model on the base scenario (which includes the travel times in the base scenario, see section 4.6.3.3), the only other inputs to this model are new travel times in the policy scenario and the calibrated OD demand matrix. The output is the calibrated OD induced demand matrix, which is essentially the calibrated OD demand matrix with the induced demand formalism of D4.1 applied to each of the demand values (Figure 31).

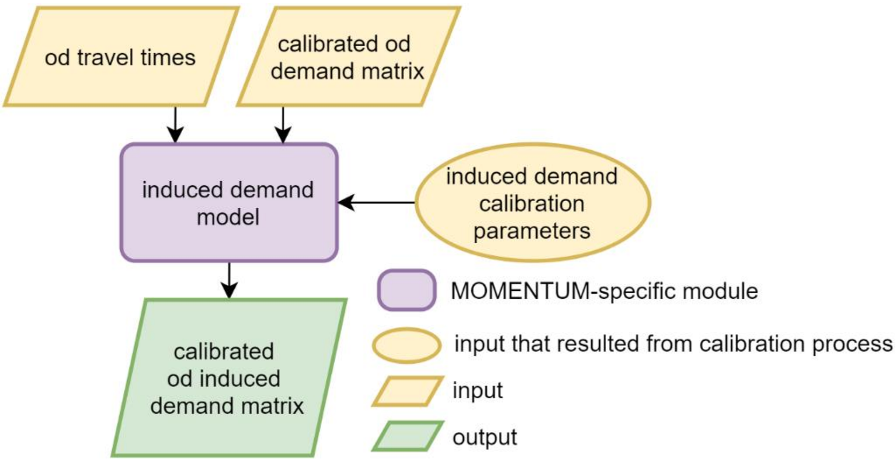


Figure 31 Schematic representation of the inputs and outputs of the induced demand model.

4.6.2.4 Overall workflow overview

In this section, the interactions between different modules in the Leuven model is described. We focus here on how the model works when applying it to a scenario, which can also be the base scenario that serves for comparison. Of course, for the model to be applied, the different modules first need to be calibrated. For non-MOMENTUM-specific modules, the calibration process was already described in the subsections of section 4.6.2.3. For the MOMENTUM-specific modules, the detailed description of the calibration and inner workings will be given in section 4.6.3.

A rudimentary overview of the interaction between different modules in the Leuven model is shown in Figure 32. The main inputs that will be changed for different scenarios are the car sharing supply and the road network. The car sharing supply is the direct input for the car ownership model, which adapts the number of cars in the synthetic population. This has in turn influence of the mode choice of the agents in the synthetic population.

The agent's mode choice is calculated using the disaggregate mode choice model. The modes people choose for their trips are directly translated in the OD demand matrices. The assignment of these OD demand matrices onto the network is done by the assignment module. This module generates new travel times, which can feed back into the mode choice model.

The assignment of the OD matrices onto the network is required for the OD demand matrix calibration. The OD demand matrix calibration can again feed back into the assignment module, or provide the input for the induced demand module, together with updated travel times. Any of the resulting OD demand matrices can always be assigned again onto the network.

The other way around, any of the assignment results can be used as input to the emission model (together with the network, which is implicitly assumed).

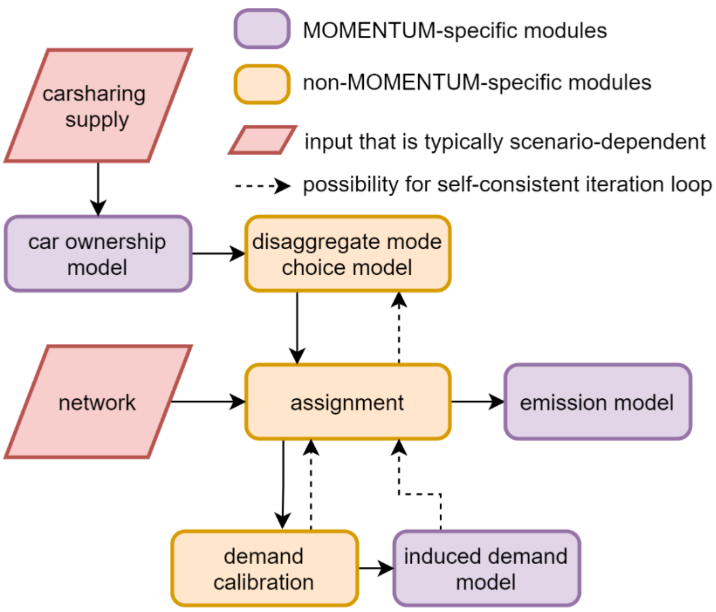


Figure 32 Overview of how the different calibrated components of the Leuven model interact with each other.

A very detailed schematic of the application of the Leuven model—including all its inputs and outputs—is shown in Figure 33. The corresponding parts of the rudimentary diagram (Figure 32) are indicated using grey boxes in the background.

The car ownership model is a disaggregate model. Since it does not depend on assignments, it can be applied to the synthetic population right from the start. Its other input is the car sharing supply. The result is an adapted car ownership for the surveyed synthetic population. Together with the non-surveyed part, this yields the full synthetic population which serves as the necessary input to the mode choice model. Additionally, the adapted surveyed population together with the car sharing supply can be used as input for the car sharing subscription model, yielding the number of car sharing subscriptions in the synthetic population. The latter can, if desired, be used again as an updated input for the car ownership model.

This mode choice model is also of disaggregate nature. It is applied for each trip of the synthetic population, taking into account the attributes of the synthetic population that makes the trips. The influence of the network on the mode choice model is indirect. Indeed, the mode choice model depends on the travel times for each trip. Those are calculated by assigning an initial OD demand matrix onto a—possibly changed—road network. The initial OD demand matrix is constructed from RVM data. Later, this initial OD demand matrix can be updated by feedback loops.

The modal shares for each trip that result from the disaggregate mode choice model can be used—together with the trip information and the external and truck OD matrices—to construct a new OD matrix. That OD matrix is calibrated using calibration factors, which were derived during the calibration process.

The resulting calibrated OD matrix can either be fed back directly into the mode choice model as to be able to use better estimates of the OD travel times. Alternatively, the induced demand model can be applied to the calibrated OD matrix, resulting in yet another new OD demand matrix, this time including induced demand quantities. Again, this calibrated OD demand matrix with induced demand can be used for updating the travel times in the disaggregate mode choice model.

Finally, the emission model can be applied. In the presented scheme, it is applied after assignment of the OD demand matrix with induced demand. However, depending on the precise scenario that is being calculated, it can be applied at any stage after assignment.

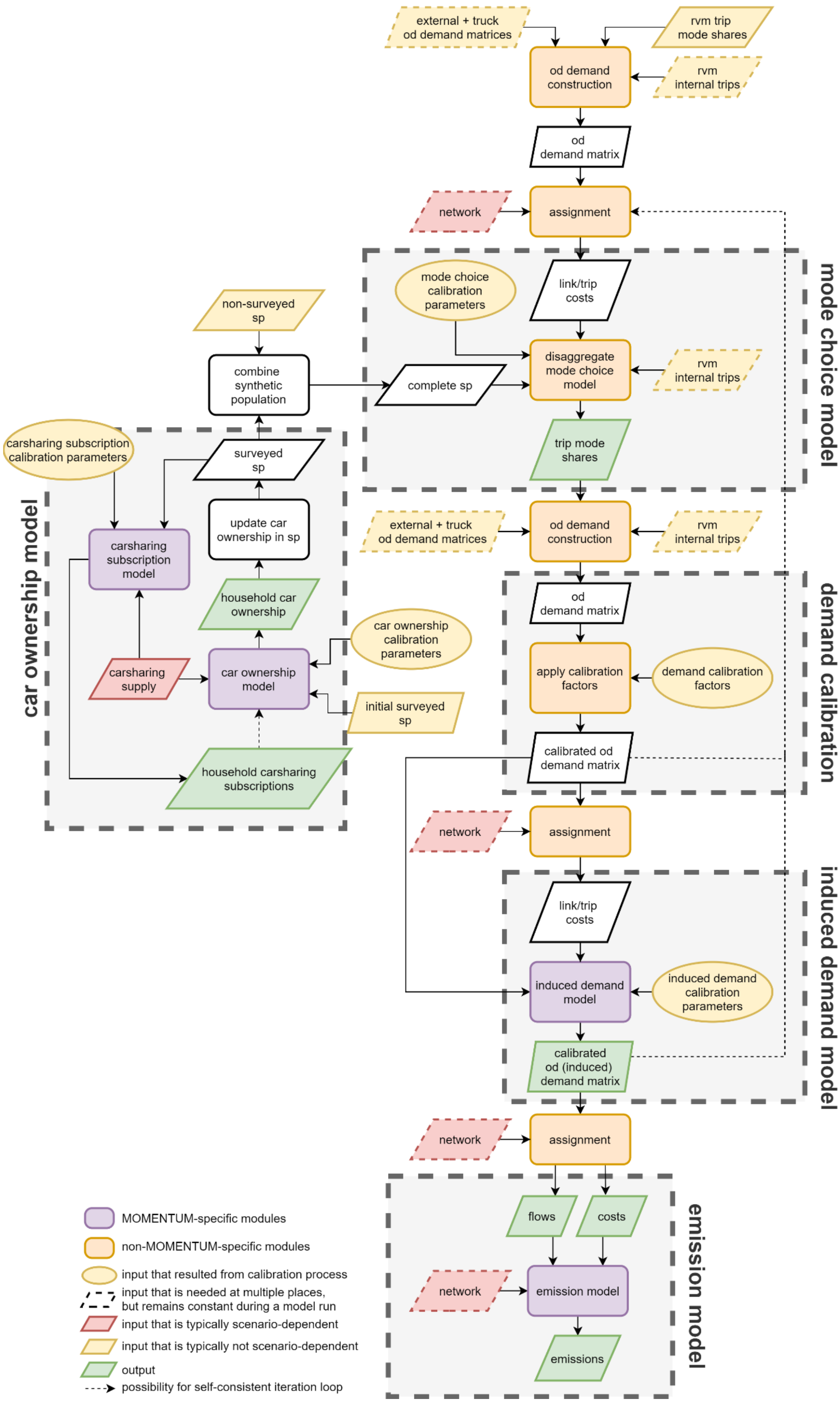


Figure 33 Detailed, exact scheme of how the different components in the Leuven model interact and interface with each other.

4.6.3 Models' implementation and calibration

4.6.3.1 Car ownership model

As described extensively in D4.1 and recapitulated briefly in section 4.6.2.3, the car ownership model makes predictions on the number of cars in a household, based on characteristics of the household and the car sharing supply in the city.

The calibration of the car ownership model is based on the city monitor survey and Leuven's car sharing supply. The procedure was detailed in D4.1. During the pre-processing of the surveyed synthetic population (see subsection 4.6.2.2)—specifically the distilling of compatible attributes and the extension with new attributes for compatibility with the car ownership model—a few inconvenient incompatibilities came up. These were solved through two small tweaks in the car ownership model's specification:

- The medium-and high-income category boundaries were changed. The new boundaries are:
  - Low income: 0–2000 euro
  - Medium income: 2000–3000 euro
  - High income: 3000–∞ euro
- The commute travel time parameter was replaced by a commute travel distance parameter.

The newly calibrated car ownership model's specification is (utility for having 0, 1, 2, or 3 or more cars in the household)

$$U_0 = 0$$

$$\begin{aligned} U_1 = {} & \beta_{\text{Belgian}} \cdot x_{\text{bln is Belgian}} + \beta_{\text{low income}} \cdot x_{\text{bln has low income}} + \beta_{\text{medium income}} \cdot x_{\text{bln has medium income}} \\ & + \beta_{\text{age}} \cdot x_{\text{age category}} + \beta_{\text{age}^3} \cdot x^3_{\text{age category}} + \beta_{\text{hh size}} \cdot x_{\text{hh size}} + \beta_{\text{cargo bike}} \cdot x_{\text{bln has cargo bike}} \\ & + \beta_{\text{pt pass}} \cdot x_{\text{bln has pt pass}} + \beta_{\text{unwilling carsharing}} \cdot x_{\text{bln is unwilling to use carsharing}} \\ & + \beta_{\text{carsharing supply subscription interaction}} \cdot x_{\text{bln has carsharing subscription}} \cdot x_{\text{carsharing supply}} \\ & + \beta_{\text{commute distance}} \cdot x_{\text{commute distance}} \end{aligned}$$

$$\begin{aligned} U_2 = {} & C + \beta_{\text{Belgian}} \cdot x_{\text{bln is Belgian}} + \beta_{\text{low income}} \cdot x_{\text{bln has low income}} + \beta_{\text{medium income}} \cdot x_{\text{bln has medium income}} \\ & + \beta_{\text{age}} \cdot x_{\text{age category}} + \beta_{\text{age}^3} \cdot x^3_{\text{age category}} + \beta_{\text{hh size}} \cdot x_{\text{hh size}} + \beta_{\text{cargo bike}} \cdot x_{\text{bln has cargo bike}} \\ & + \beta_{\text{pt pass}} \cdot x_{\text{bln has pt pass}} + \beta_{\text{unwilling carsharing}} \cdot x_{\text{bln is unwilling to use carsharing}} \\ & + \beta_{\text{carsharing supply subscription interaction}} \cdot x_{\text{bln has carsharing subscription}} \cdot x_{\text{carsharing supply}} \\ & + \beta_{\text{carsharing supply}} \cdot x_{\text{carsharing supply}} + \beta_{\text{commute distance}} \cdot x_{\text{commute distance}} \end{aligned}$$

$$\begin{aligned} U_3 = {} & C + \beta_{\text{Belgian}} \cdot x_{\text{bln is Belgian}} + \beta_{\text{low income}} \cdot x_{\text{bln has low income}} + \beta_{\text{medium income}} \cdot x_{\text{bln has medium income}} \\ & + \beta_{\text{age}} \cdot x_{\text{age category}} + \beta_{\text{age}^3} \cdot x^3_{\text{age category}} + \beta_{\text{hh size}} \cdot x_{\text{hh size}} + \beta_{\text{cargo bike}} \cdot x_{\text{bln has cargo bike}} \\ & + \beta_{\text{pt pass}} \cdot x_{\text{bln has pt pass}} + \beta_{\text{unwilling carsharing}} \cdot x_{\text{bln is unwilling to use carsharing}} \\ & + \beta_{\text{carsharing interaction}} \cdot x_{\text{bln has carsharing subscription}} \cdot x_{\text{carsharing supply}} \\ & + \beta_{\text{carsharing supply}} \cdot x_{\text{carsharing supply}} + \beta_{\text{commute distance}} \cdot x_{\text{commute distance}} \end{aligned}$$

with the parameters given in Table 7.

Table 7: Disaggregate car ownership model calibration parameters. The log likelihood of this final result is -940.49.

calibration parameter	# cars	value	S.E.	z-val
intercept C	2	-1.248	0.502	-2.489
	3	-2.843	1.223	-2.325
$\beta_{Belgian}$	1	1.868	0.27	6.909
	2 & 3	2.098	0.382	5.497
$\beta_{low\ income}$	1	-1.422	0.26	-5.476
	2 & 3	-3.393	0.43	-7.893
$\beta_{medium\ income}$	1	-0.701	0.269	-2.607
	2 & 3	-1.671	0.313	-5.331
β_{age}	1 & 2	-0.524	0.15	-3.485
	3	-1.079	0.343	-3.144
β_{age^3}	1 & 2	0.015	0.003	4.599
	3	0.027	0.006	4.406
$\beta_{hh\ size}$	1	0.526	0.09	5.821
	2	0.894	0.104	8.631
	3	1.173	0.148	7.921
	1	-0.717	0.395	-1.818

$\beta_{cargo\ bike}$	2	-2.22	0.482	-4.606
	3	-3.125	1.132	-2.762
$\beta_{pt\ pass}$	1	-0.909	0.221	-4.12
	2 & 3	-1.328	0.254	-5.222
$\beta_{unwilling\ carsharing}$	1	0.676	0.218	3.107
	2	1.114	0.257	4.335
	3	1.465	0.445	3.291
$\beta_{carsharing\ interaction}$	1 & 2 & 3	-0.121	0.022	-5.37
$\beta_{carsharing\ supply}$	2	-0.042	0.02	-2.102
	3	-0.085	0.045	-1.891
$\beta_{commute\ distance}$	1	0.014	0.006	2.357
	2 & 3	0.024	0.007	3.605

The description and interpretation of the parameters as given in D4.1 still holds similarly here. Even though some small changes were made to the model as compared the one in D4.1, the estimated values for the calibration parameters remain very similar. This demonstrates the robustness of the car ownership model.

The car ownership model can only be applied to the surveyed synthetic population, because extrapolating the model to regions outside of Leuven—for which it is not adequately calibrated—could give misleading results. Moreover, the extended synthetic population attributes are only available inside the surveyed areas.

The car ownership model should not be applied to households with the displaced student household type. As explained before, these are students that live in Leuven during the week, but still have some of their attributes determined by their parents' household. The inapplicability of the model to these agents is not a large drawback, as the student population does not often own a car by themselves nor make use of car sharing systems.

During the implementation of the car ownership model, it was found favourable to not only be able to calculate a household's car ownership upon a change in car sharing supply, but also whether households have a car sharing subscription. This model—inspired by the car ownership model itself—was implemented as a post processing step and uses in addition to the output of the car ownership model also the same inputs. The car sharing subscription model is of binomial logit type and was iteratively calibrated using PandasBiogeme (Bierlaire, 2020). Its utility specification is (0 = has no carsharing subscription, 1 = has a car sharing subscription)

$$U_0 = C$$

$$\begin{aligned} U_1 = C &+ \beta_{\text{unwilling carsharing}} \cdot x_{\text{bln is unwilling to use carsharing}} + \beta_{\text{carsharing supply}} \cdot x_{\text{carsharing supply}} \\ &+ \beta_{\text{0 cars hh}} \cdot x_{\text{bln hh has 0 cars}} + \beta_{\text{1 car hh}} \cdot x_{\text{bln hh has 1 car}} + \beta_{\text{cargo bike}} \cdot x_{\text{bln has cargo bike}} \\ &+ \beta_{\text{large hh}} \cdot x_{\text{bln hh size} \geq 6} + \beta_{\text{one person hh}} \cdot x_{\text{bln hh size} = 1} \end{aligned}$$

The calibrated parameters and their interpretation are listed in Table 8.

Table 8: Calibration parameters of the car sharing subscription model. The calibration is based on 1404 samples. The log likelihood of this final result is -248.31 and the adjusted ρ^2 is 0.737.

calibration parameter	bln car sharing subscription	value	t-statistic	interpretation
intercept C	0	0	NA (fixed value)	
	1	-3.67	5.94	
$\beta_{\textit{unwilling carsharing}}$	1	-2.42	-6.52	When unwilling to use car sharing, one is not likely to have a car sharing subscription.
$\beta_{\textit{carsharing supply}}$	1	0.0514	1.42	The probability of having a car sharing subscription increases with the car sharing supply in one's neighbourhood.
$\beta_{\textit{0 cars hh}}$	1	1.84	4.76	One is more likely to have a car sharing subscription when the household does not own any cars.
$\beta_{\textit{1 car hh}}$	1	0.832	2.3	Also, when the household owns only 1 car, one is more likely to have a car sharing subscription.
$\beta_{\textit{cargo bike}}$	1	0.804	2.24	Households with a cargo bike are more likely to have a car sharing subscription. The car sharing service is probably used for trips or activities that are not possible with the cargo bike.

$\beta_{large\ hh}$	1	1.2	3.27	Larger households are more likely to have a car sharing subscription. Either because there are more people in the household that can have a subscription, or as a substitute for an additional car in the household.
$\beta_{one\ person\ hh}$	1	-1.13	-2.73	Households consisting of only one person are less likely to have a car sharing subscription. Note, however, that if this household does not own a car, the net effect on the utility is still positive. The net effect Is negative if the household already owns a car.

In the case studies, the car ownership model and car sharing subscription extension will be used to assess scenarios in which the effects of a changed car sharing supply are investigated. The model shall first be applied to the parameters of a base scenario, the results of which will act as a baseline measure. Different future and policy scenarios can then be assessed. The inputs of the model can be directly retrieved from the overall model (Figure 29 and Figure 33). The outputs are probabilities for each household of having a certain number of cars and having a car sharing subscription. Since these probabilities are known at a disaggregate level, it will be possible to perform further socio-demographic analysis on the results.

4.6.3.2 Emission model

An in-depth description of the calibration of the emission model was already provided in D4.1. The calibrated model allows to calculate emissions for traffic assigned to a network in any of 31 EU member countries for any year between 2016 and 2050. The results are emission figures that account for the fleet composition and traffic speeds on the network.

The required emission model inputs are the car flows for each link, the corresponding lengths and car travel times for these links (Figure 30). These inputs follow directly from the Leuven case study inputs or from other modules of the traffic model (Figure 33). The year and EU member county are of course fixed by the scenario at hand. The model returns the CO, CO_2, NO_x, PM, and VOC emissions exhausted by cars for each link. These emissions can be further aggregated to calculate the emissions in any desired area.

The emission model will be used in the Leuven case study scenarios to assess the impact of shared mobility services and related policies on the level of regular car traffic emissions. Similar to the car ownership model, the outputs of a base scenario will be compared to those of a future or policy scenario. Except for being interesting on their own, the emission model results can later be used as input for models in other fields, such as economics, climate and environment.

4.6.3.3 Induced demand model

The theory and rationale of the induced demand model was explained in D4.1. In the Leuven case study, the logit formulation for induced demand will be used to improve predictions when the car travel time changes drastically (e.g., because of policy measures taken to promote shared mobility). The model will be calibrated based on the car travel time-elasticity of demand.

The calibration of the induced demand model is based on

- the calibrated od demand matrix of a selected base scenario;
- a representative car travel time-elasticity of car demand η_{car}. As indicated in section 4.6.2.1, the short-term direct time-cost elasticity for car travel demand is set to $\eta_{\text{car}} = -0.6$ (de Jong, 2001);
- the disaggregate mode choice calibration parameters, which are calculated during the calibration of the disaggregate mode choice model. Specifically, we need the mode utility coefficient for the mode travel time $\beta^{\text{mode}}_{\text{travel time}}$.

The detailed steps that are followed for the calibration process are shown in Figure 34. It boils down to applying the formula for the calibration parameter K as it was given in D4.1. However, a slight inconvenience arises because we apply the induced demand model on the aggregated OD matrices, while our mode choice model that we estimated earlier is applicable to disaggregated trips. This inconvenience is circumvented by using the same mode travel time parameters $\beta^{\text{mode}}_{\text{travel time}}$ at the aggregate level. For each OD, this allows to fit a mode-specific additive utility constant C^{mode} in the aggregated mode utility $U^{\text{mode}} = \beta^{\text{mode}}_{\text{travel time}}\, t^{\text{mode}} + C^{\text{mode}}$. The constant is chosen such that the multinomial logit model applied to these aggregated mode utilities results in the correct aggregated OD demand mode shares.

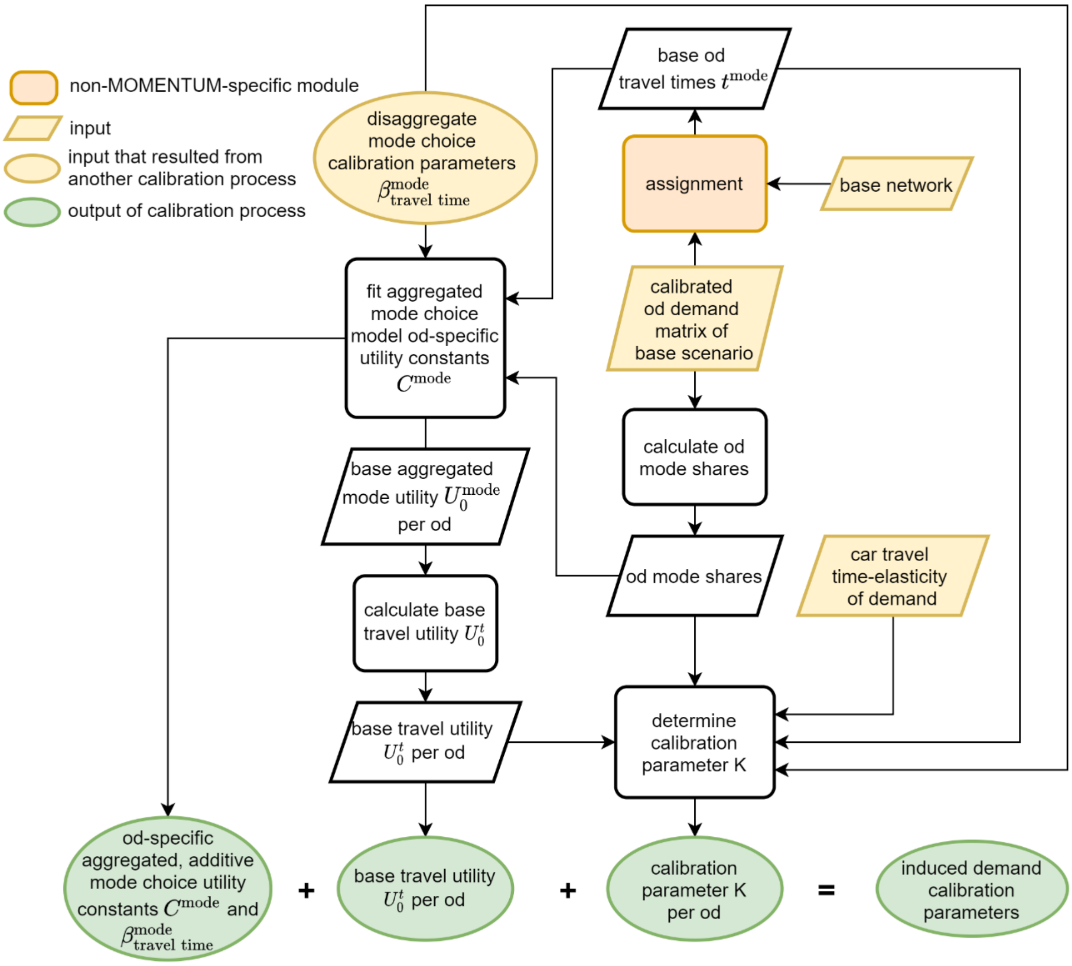


Figure 34 Induced demand model calibration process. The od-specific aggregated additive mode choice utility constants C^{mode} and travel time parameters $\beta^{mode}_{travel\ time}$ together with the base travel utility U_0^t and calibration parameter K per OD pair are called the induced demand calibration parameters.

The formulae to determine the base travel utility U_0^t as the log sum over the base mode utilities U_0^{mode} and to determine the final calibration parameter K can all be found in D4.1. These additive utility constants C^{mode}, travel time parameters $\beta^{\text{mode}}_{\text{travel time}}$ and log sum base scenario travel utility U_0^t are also part of the induced demand calibration parameters, since scenarios need to be calculated using the same aggregated mode choice utility formula and relative to the same base scenario utility as on which calibration was performed.

In D4.1, we also indicated that, in order to successfully calibrate the logit-like induced demand model, the calibration parameter K must be positive. This further translates into the condition $t^{\text{car}}|\beta^{\text{car}}_{\text{travel time}}| > |\eta_{\text{car}}| > (1\text{-}P_0^{\text{car}})\ t^{\text{car}}|\beta^{\text{car}}_{\text{travel time}}|$. Obviously, the induced demand model should only be applied to the OD relations for which this condition is satisfied.

The steps in applying the induced demand model are shown in Figure 35. The only new parameters that are necessary are the new scenario's travel times and its calibrated OD matrices. The travel times are used to calculate new travel utilities. Together with the induced demand calibration parameters and the calibrated OD matrices of the new scenario, this allows to calculate the induced demand with the formulae stipulated in D4.1.

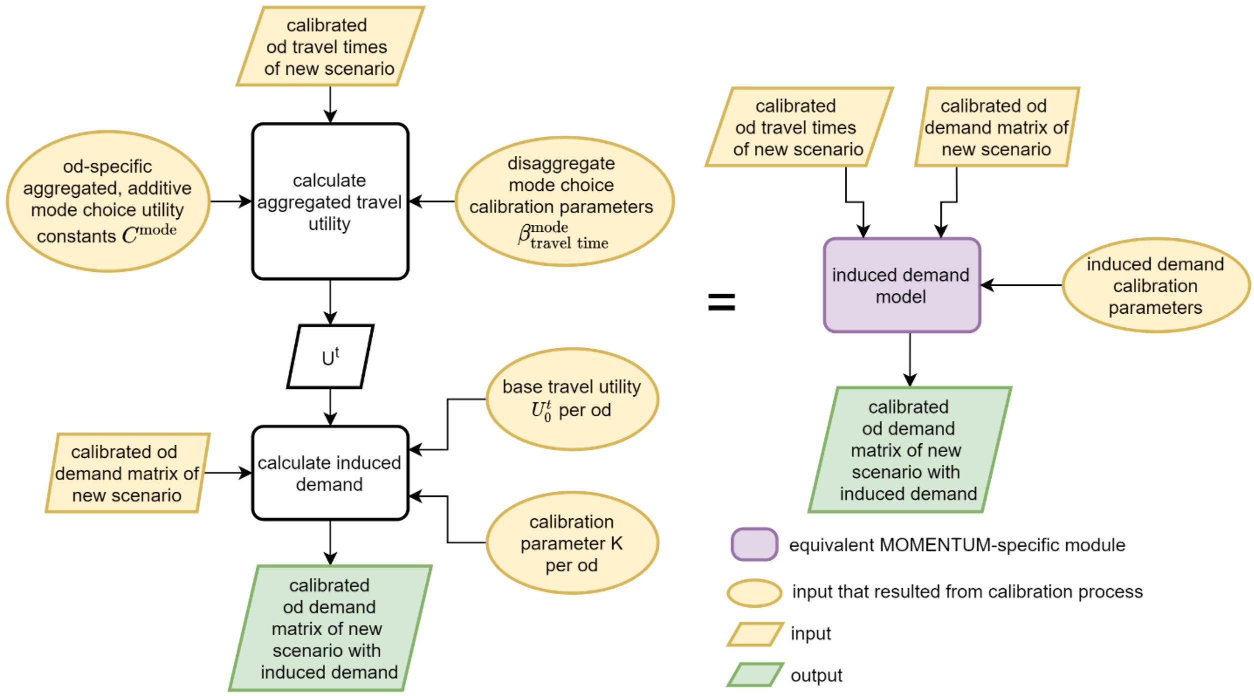


Figure 35 Application of the induced demand model. Left shows in detail where all (calibration) inputs are used. Right shows the equivalent model, as it is used in the overall Leuven model that was presented in section 4.6.2.4. This is the same diagram as the one presented in Figure 31.

When applying the induced demand model on the Leuven case studies, we will focus on the external OD pairs. By applying the induced demand model there, we partially compensate for the fact that these OD relations do not support mode choice. Additionally, the induced demand model may also be applied to internal OD relations that exhibit strongly altered travel times in the new scenario.

5 Conclusions

The developed interactive Decision support tool in the WP5 is a scientific framework for assessing and evaluating emerging mobility services. D5.3 describes the implementation of the enhanced simulation tools resulting from D5.1 and the decision support dashboard developed in D5.2 in the four case study cities. The interactive DST supports the formulation, assessment and comparison of different policy alternatives, by facilitating the interpretation, analysis and communication of the simulation results. The dashboard visually presents new data sources and enhanced modelling engines delivered by MOMENTUM. A fully calibrated transport model was developed for Madrid, Thessaloniki, Leuven and Regensburg.

The simulation models were calibrated using the supply and demand data collected or produced in WP3. The policies under consideration and the KPIs produced by the DST, will be tailored to the specific requirements of each city. The implementation in the city of Thessaloniki was used as a testbed for the implementation in the rest of the cities. The new toolset is implemented on top of the existing mobility ecosystem, which holds a variety of data analysis and simulation tools allowing the cooperation of public and private institutions and has become a real-life conditions testbed for innovative mobility solutions. The work conducted in WP5 includes both the enhancement of existing transport simulation tools and the development of visually-aided interactive tools integrating the outputs of the simulation tools with other data analysis capabilities for mobility planning, monitoring and management. Furthermore, guidelines about the methodology to be followed for every step, were given to the partners in order to make the procedure of validation and calibration more explanatory. All levels were tested in the real testbeds and the improvements suggested are described in this document.

It is clear from this document that all city partners tested services applicable to their needs and questions asked in previous WPs. The aim of the DST is to provide cities with a tool that can be applicable in all cases. The automated procedures followed in Level 1 might lead to a certain level of adaptability for every case examined. The model developed in Level 1, gives the user the ability to easily test different services by having a small amount of input data, although fine tuning of this level might be needed in order to meet each city's expectations and special characteristics. Hence, as the model was developed based on the testbed of Thessaloniki, input variables and constraints might need to be adapted in order to produce the most accurate approximations of the tested services. In Level 2, the level of detail of the input data and algorithms used, leads to concrete and city approach outcomes. OD matrices and car data information can be imported in Level 2, giving an extended and more analytical use of the tool. The implementation of Level 3 leads to more accurate results due to the utilisation of advanced methods and algorithms for the modelling and evaluation of the shared mobility services. The level of detail of input data needed for this level, can lead to more accurate results. Although the amount of preparation work needed for this level is increased, the examined services can be city oriented. Thus, the calibration and validation of the models involved in Level 3, require more effort to be implemented, in order to focus on the targeted scenarios of each city.

In conclusion, Deliverable 5.3 is the last component of the WP5. This document includes all the findings deriving from previous deliverables (5.1 and 5.2) and WPs, summarizing methodologies and procedures followed in each case studies, in an integrated Decision Support Toolset. The toolset developed will tackle the needs of policy and decision makers identified in WP2 and is based on the outputs and capabilities of the new data analysis and modelling techniques developed in WP3 and WP4, respectively. Complexity and interaction of different sources of input data, used in the development of the DST, alongside with the evaluation of the proposed methodologies through the assessment of the set of policy measures, constitutes an important step towards WP6. The goal of WP6 is to demonstrate and evaluate the capabilities of the new data collection methods, simulation models and planning support tools in a real operational context. The tools developed in WP5 will be used to forecast the expected impact of such policies under a range of possible futures, and the model results will be reviewed and discussed with policy makers, mobility service providers and other relevant stakeholders.

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7 Annex

In the Annex of this document are presented the values of the tests performed from all the cities, for the available services of Level 1. Every city performed and tested the services that they were included, based on the scope of MOMENTUM project. Thus, not values for all city partners are included in the tables following. All tests were performed on the online DST.

Once the initial version of the tool was developed, city partners performed test, based on the characteristics and values of each case. CERTH, receiving the feedback and the comments from city partners, added the proposed improvements to the tool. Thus, values that are included in the tables below as N/A (Not Available) refer to parameters that were imported once the calibration and validation task was done by the cities. Finally, it is important to be mentioned that values of population and square meters of the area of interest are automatically retrieved from MOMENTUM's repository.

Service: vehicle sharing (bike station)

Area of interest		Cost of operation					Socio-economic and functional variables						Constraints		Decision variables	
City	Area	Bicycle operating cost per km	Bicycle depreciation cost per hour	Operator cost per hour (per station)	Dock depreciation cost per hour	Weight assigned to the user	Value of time of users	User walking speed	Bicycles travel speed	Mean demand of the area	Standard deviation of demand of the area	Travel time activation	Maximum waiting time	Maximum walking time	Number of stations	Number of docks
Thessaloniki		0.1	0.1	1	1	0.5	6	5	12	50	8	YES	3	8	1 to 21	1 to 40
Thessaloniki		0.3	0.1	1	1	0.5	6	5	12	50	8	YES	3	8	1 to 21	1 to 40
Thessaloniki		0.1	0.1	1	1	0.5	6	5	12	50	8	YES	6	8	1 to 10	1 to 40
Thessaloniki		0.1	0.1	1	1	0.5	6	5	12	50	8	YES	3	8	1 to 20	1 to 15
Regensburg		0.13	0.08	0.19	0.01	0.5	6	5	12	800	50	0	6	6	30-150	10-20
Regensburg		0.13	0.08	0.19	0.01	0.5	6	5	12	800	30	0	5	5	61-92	8-12
Regensburg		0.13	0.08	0.19	0.01	0.5	6	5	12	400	30	0	6	5	1-91	1-25
Madrid		0.261	0	0	0		5	5	18	430	125	NA	3	5	41-91	1-25
Madrid	Arganzuela	0.261	0	0	0		5	5	18	24	4	NA	3	5	1-91	1-25
Madrid	Salamanca	0.261	0	0	0		5	5	18	25	6	YES	3	5	1-50	1-25
Madrid		0.261	0	0	0		5	5	18	430	125	YES	3	5	20-300	10-30
Leuven		0.1	0.1	1	1	0.5	6	5	12	50	8	YES	3	8	1 to 21	1 to 40

Service: On demand (taxi - ride sharing)

		Cost of operation			Socio-economic and functional variables			Constraints		Decision variables		Run the sensitivity module for demand
City	Area	Operator cost per kilometer	Operator cost per hour (per car)	User costs weight	Value of time of users	Vehicle speed	Mean demand of the area	Maximum waiting time	Detour delay factor	Number of vehicles available for the service	Number of passengers	
Thessaloniki		0.5	15	0.5	15	35	200	5	10%	NA	NA	NA
Thessaloniki		0.5	15	0.5	35	35	200	2	5%	NA	NA	NA
Thessaloniki		0.5	15	0.5	15	35	200	5	10%	1 to 100	1 to 100	110 to 120
Thessaloniki		0.5	15	0.5	35	35	200	5	5%	1 to 100	1 to 100	110 to 140
Regensburg		0.5	15	0.44	15	50	100	3	8%	1 to 19	1 to 25	

Service: vehicle sharing (scooters floating)

		Cost of operation			Socio-economic and functional variables					Constraints	Decision variables	Run the sensitivity module for demand
City	Area	Operator cost per kilometer	Operator cost per hour (per scooter)	User costs weight	Value of time of users	Users Walking Speed	Escooter Travel speed	Mean demand of the area	Travel time activation	Maximum walking time	Number of Escooters	
Thessaloniki		0.2	0.5	0	15	5	15	200	NA	2	1 to 100	NA
Thessaloniki		0.2	0.5	0	15	5	15	200	NA	2	20 to 80	NA
Thessaloniki		0.2	0.2	0	20	5	15	200	NA	2	20 to 80	NA
Thessaloniki		0.2	0.5	0	15	5	15	200	YES	2	1 to 100	110 to 120
Thessaloniki		0.2	1	0	15	5	15	200	YES	2	50 to 200	110 to 120

Service: On demand (DRT)

		Cost of operation			Socio-economic and functional variables					Constraints			Decision variables	Run the sensitivity module for demand
City	Area	Operator cost per kilometer	Operator cost per hour (per bus)	User costs weight	Value of time of users	Bus cruise Speed	Bus acceleration	Boarding/alighting time	Mean demand of the area	Detour delay factor	Maximum waiting time	Maximum number of buses	Frequency	
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	200	2	0.25	5	NA	NA
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	200	4	1	10	NA	NA
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	300	2	0.25	5	NA	NA
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	100	2	0.25	5	NA	NA
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	200	2	0.25	5	0.1 to 1	110 to 120
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	100	2	0.25	5	0.1 to 1	110 to 120
Thessaloniki		0.5	15	0.5	15	25	12000	0.05	100	2	0.25	5	0.1 to 1	150 to 200

