Deliverable

D3.4 Smart City domains, models and interaction frameworks v2

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Table of Contents

1 Executive Summary 6
2 Introduction: scope and goal of this report 8
3 Smart City domains and their interactions in digital twins 9
3.1 Broader overview of smart city domains and how they interact 9
3.2 The role of digital twins 9
3.3 Traffic-centered focus in DUET digital twin 10
3.4 Scope and resolution levels in traffic-centered urban digital twins 12
3.5 Synchronization of an urban digital twin 14
4 SC Domains and models and their integration within DUET 16
4.1 Initial status of domain models and their integration before DUET 16
4.1.1 The DUET models 16
4.1.1.1 Static traffic models (KUL) 16
4.1.1.2 LTM dynamic traffic assignment model (KUL) 17
4.1.1.3 Traffic Modeller static traffic model (P4All) 17
4.1.1.4 NoiseModelling (P4All) 17
4.1.1.5 Urban Strategy air quality and noise models (TNO) 18
4.1.1.6 CityFlows local traffic model (IMEC) 18
4.2 Ambitions and scope of DUET 20
4.3 Achievements of DUET model interaction 22
4.3.1 Enhancements to the interacting models 23
4.3.1.1 KUL: Dyntapy: integrated static and dynamic traffic assignment and demand generation 23
4.3.2 Interaction of DUET models 24
4.3.3 Interaction of DUET models and data: towards automated model configuration 24
4.3.4 Easy integration of future improvements to DUET models 25
5 Beyond DUET: some reflections on future development of urban Digital Twins 26
5.1 Digital Twin user needs beyond DUET 26
5.1.1 Development directions of domain models already integrated in DUET: mobility, traffic & traffic impact 26
5.1.2 Development directions of domain models not yet integrated in DUET: challenges across multiple Smart City domains 27
5.1.3 Ontology for urban digital twins: towards a deeper integration of DUET models and data 28

5.2 Broader support of case and scenario management and control 29
5.2.1 (Semi-)automated set up and calibration of UDT models/cases 29
5.2.2 enhanced scenario management, optimization, control, and analysis 30
6 Conclusion 31
Annex A Dyntapy traffic assignment 34
A.1. Introducing Dyntapy 34
A.2. Platform Integration 35
A.3. Performance Issues in DTA 36
A.4. Modelling of intrazonal flows 36
Annex B: Poidpy demand generation tool 38
B.1. Introduction 38
B.2. Methodology 41
1. Study area definition 41
2. POI data extraction and preprocessing 41
3. Creation of unidimensional POI-layers 44
Residential layer 44
Activity layer 45
4. Trip Generation 48
5. Trip distribution 49
B.3. Model calibration 49
Trip generation model 51
Trip distribution model 52
B.4. Results 54
Antwerp 54
Trip generation 54
Trip Distribution 56
Ghent 60
Trip Generation 61
Trip distribution 65
Athens 68
Trip generation 68
Trip distribution 70
B.5. Discussion 72
B.6. Conclusion 73

B.7. Appendices 74
Appendix B1 74
Appendix B2 75

1 Executive Summary

This deliverable is an update and complement of "D3.3: Smart City domains, models and interaction frameworks v1". That report described the models that the technical partners (namely TNO, P4ALL and KUL) provided as input to integrate into the DUET digital twin: models for private Traffic, Air Quality and Noise. Some models needed modifications or development of additional modules for integration in DUET, notably the static and dynamic traffic models by KUL and the demand generation tool; these developments are reported in this document.

The report starts with a broader review in Chapter 3 of Smart City domains as candidates for integrating models in an urban Digital Twin. It elaborates on traffic-centered models and traffic-related impact models and discusses how – even in this single Smart City domain – a variety of submodules and interactions need to be captured. The current traffic models in DUET, for instance, focus on the operational level where the impact of route choice on loads and externalities (air quality, noise) can be investigated. Other decisions like modal choice, departure choice and activity location choice, as well as other activity and spatial decisions at the demand side of person mobility, require complementary model sets. The report creates awareness of the trade-offs that need to be made between broader scope and higher resolution. Moreover, even at high resolution, any traffic model will inevitably be more valid in predicting aggregate flows (e.g. at major roads like arterials and motorways) as compared to local traffic. A final general discussion on Smart City domains in digital twins is that of synchronization frequency with the physical world: the models require different data and calibration techniques, depending on its use is intended for second-to-second real-time tracking for short-term prediction, day-to-day tracking for next-day predictions, or tracking of slow-moving changes for strategic impact of changes to infrastructure or activities.

The focus of Chapter 4 then shifts to the digital twin domains and models specifically within DUET. It recapitulates the available traffic and traffic impact models:

- Static Traffic Assignment modules of KUL
- LTM Dynamic Traffic Assignment model of KUL
- Traffic Modeller static traffic assignment of P4All
- NoiseModelling of P4All
- Urban Strategy air quality and noise model of TNO
- CityFlows local traffic model of Imec

Scope and resolution levels of these models are compared to the user needs (epics and user stories) resulting from the stakeholder consultation that was reported in deliverables D2.2 & 2.3 of DUET. We conclude that the match is still partial: while impact models need little modification and indeed users see added value in the integrated consultation of (multiple) traffic models and traffic impact models, for some user stories, the scope of traffic models should evolve towards a higher level of detail (more local scope), and towards inclusion of alternative modes to car travel (ideally including parking, modal shift and multimodal trip making).

For integration into the DUET platform, some models required modification. The report describes the integration of KUL's separate Static and Dynamic Traffic Assignment modules into an uniform package Dyntapy; for all models a model client and technical interaction framework was created. To facilitate the set up and calibration of new cases (e.g. integrate new cities into DUET), a network and demand generation module has been developed that auto-configures an initial traffic model for the given case, which then needs further calibration and fine-tuning.

With the domain models of Chapter 4 integrated in DUET, an outlook is made in Chapter 5 of desired developments and user needs beyond DUET. This entails development directions for the models already included in DUET towards more fine-grained validity, multi-period assessment, and a wider variety of outputs. But also inclusion of complementary aspects within the traffic and mobility domain (e.g. parking, transit, pedestrians, cyclists, mobility as a service) and in connected Smart City domains like population modeling, city logistics, housing/land-use, energy system. Such endeavor would require development of a broader urban digital twin ontology formally describing all relevant entities and their properties that models and data should quantify in existing and what-if scenarios. Finally, some advanced digital twin functionality is proposed for supporting the users in setting up cases and scenarios, and optimizing their decision variables for achieving their objectives.

2 Introduction: scope and goal of this report

This deliverable is an update and complement of "D3.3: Smart City domains, models and interaction frameworks v1". That report described the models that the technical partners (namely TNO, P4ALL and KUL) provided as input to integrate into the DUET digital twin: models for private Traffic, Air Quality and Noise. Some models needed modifications or development of additional modules for integration in DUET, notably the static and dynamic traffic models by KUL and the demand generation tool; these developments are reported in this document.

In this stage of the DUET project, partners have now gained experience with integrating these tools and had internal and external discussions with potential users about epics and user stories as expressed in D2.2 and D2.3. This report reflects on the requirements these epics and user stories set to the DUET models and on the achievements of DUET as a first-of-its-kind platform for interaction and integration of data and the domain models currently connected. Such a state of affairs also allows making an overview of desired further development of urban DIGITAL TWIN and of DUET more specifically. These future needs include:

- further refinement and functionality of existing models;
- extension towards inclusion of new complementary models that enable new use cases beyond what DUET already offers;
- deeper integration of existing models and data;
- broader support of case and scenario management and control.

This report is structured as follows. Chapter 3 reviews in a broad sense which Smart City domains exist as candidates for integrating models in an urban Digital Twin. It elaborates on traffic-centered models and traffic-related impact models and discusses how – even in this single Smart City domain – a variety of submodules and interactions need to be captured. It discusses the trade-offs that need to be made between broad scope and high resolution. Finally, it discusses the possible synchronization frequencies of the digital twin to its physical counterpart in relation to its prediction horizons and the corresponding challenges for careful calibrating of the models. While Chapter 3 takes a general urban digital twin perspective, Chapter 4 focuses specifically on DUET. It recapitulates the available traffic and traffic impact models and extracts from the user epics and stories the requirements that DUET models should ideally meet. It continues by discussing progress made in DUET to address these needs, both by enhancements to the models themselves, their integration, and their interaction with the DUET data sources. Chapter 5 reflects critically on developments and user needs beyond the current version of DUET. Given the broad and open character of Smart City domains, a digital twin environment should naturally grow and evolve to become more performant, more tailored to user needs and to cover and integrate more Smart City Domains. The chapter reflects on further developments to the models already present in DUET, inclusion of related-domain models, and more advanced support that a digital twin could offer to its users to set up, manage and control cases and scenarios. Finally, Chapter 6 concludes this report.

3 Smart City domains and their interactions in digital twins

3.1 Broader overview of smart city domains and how they interact

In Smart Cities, many domains interact. Figure 1 gives some representations of interacting domains from four different sources. In each of them, smart mobility or transportation is among the main domains, along with buildings, spatial planning, water and environmental management etcetera. It shows why DUET has chosen traffic and traffic-related impacts as a first domain to be integrated in the urban digital twins, but also how this can only be considered the start of a more encompassing development that should evolve towards inclusion of all related Smart City domains shown in Figure 1. Indeed, while for most of the individual domains, models, data, technology and dashboards exist that allow stakeholders to understand the current status and what-if scenarios of each domain separately, the strength of a digital twin lies in making these uniformly available to more stakeholders, and to address cross-domain challenges for which an integrated analysis and exploration is required.

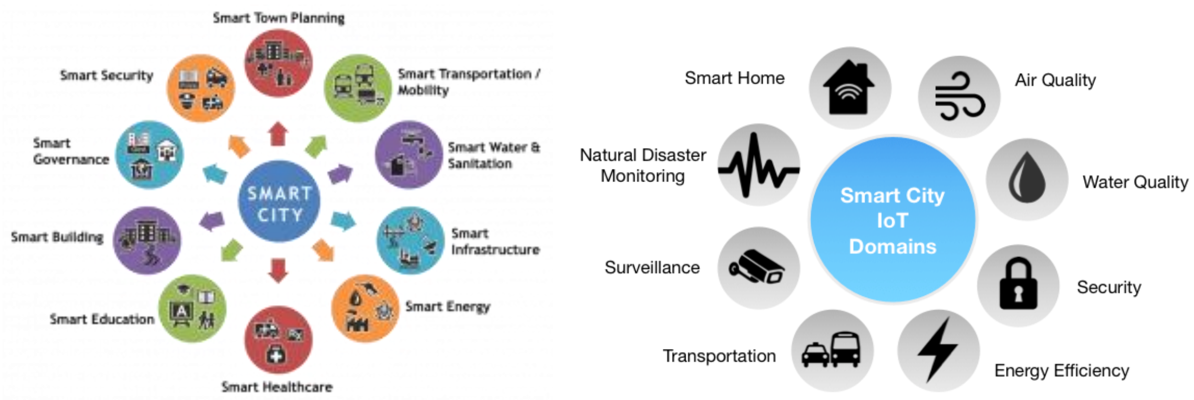

Figure 1: Smart city domains[1][2]

3.2 The role of digital twins

For most of the domains depicted in Figure 1, domain-specific models, data-platforms and KPI dashboards exist as a support for decision making by stakeholders. However, each domain is an open system that interacts with the other, which is disregarded in the available decision support instruments. Digital twins can support evidence-based cross-domain decision making in the public and private environment, by integrating domain-

[1] Krinichansky, K.V., 2019. Smart Solutions for Smart Cities, in: S. Sergi, B. (Ed.), Tech, Smart Cities, and Regional Development in Contemporary Russia. Emerald Publishing Limited, pp. 151–175. https://doi.org/10.1108/978-1-78973-881-020191010

[2] Nassar, A.S., Montasser, A.H., Abdelbaki, N., 2018. A Survey on Smart Cities' IoT, in: Hassanien, A.E., Shaalan, K., Gaber, T., Tolba, M.F. (Eds.), Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2017, Advances in Intelligent Systems and Computing. Springer International Publishing, Cham, pp. 855–864. https://doi.org/10.1007/978-3-319-64861-3_80

specific data sources and models in a single environment and making these available to policy makers, civil servants, investors, developers, creative citizens to engage the community to enrich the data and develop new services. It supports monitoring, exploring what-if simulations, but is also a tool for measurement of effects. By providing insight into data and cross-domain analysis of data, it is also an opportunity for the Urban Digital Twin as a communication tool to citizens.

The role of models in a digital twin (in addition to data) is:

- to interpolate spatially where no direct measurement data is available;
- to integrate the presentation and analysis of complementary data sets;
- to cross-correlate data from different domains;
- to infer properties/attributes that are not directly measured;
- to convert measurements and state info into KPIs;
- to extrapolate (predict) business as usual (BAU) and what-if scenarios.

3.3 Traffic-centered focus in DUET digital twin

Of the various interacting domains of the Smart City discussed in 3.1, DUET focuses on traffic-related domains – a focus that calls for expansion to other domains upon future development of DUET (section 5.1.2).
The transportation system is an open system, where travelers of different population segments interact in different transportation modes to enable different types of activities. There exists no single all-encompassing way of modeling all these interactions. Rather, a multitude of model components exist that can be combined into a whole range of transport models.

Figure 2 brings some structure into the cause-and-effect relationships within transportation systems, and therefore in the many existing models and model components. It shows how the demand for mobility is linked to interactions at the socio-demographic level. A whole series of decisions converts the demand for mobility into specific demands for trips along specific routes. At the operational level, finally, these trips come together in the transport infrastructures, which determines the locally observed flows and delays along every road and intersection in the network. The stakeholders involved in transportation can evaluate the resulting traffic patterns from various perspectives, like the time cost, environmental impact, safety cost etcetera. Note how many feedback mechanisms connect phenomena on one level in the transportation system to other levels, which creates dynamic interactions on the short, medium, and long term. Also, it means that typically the impact of any change within the transportation system or one of its boundary conditions does not remain local, but trickles down or up to many related parts of the transportation system.

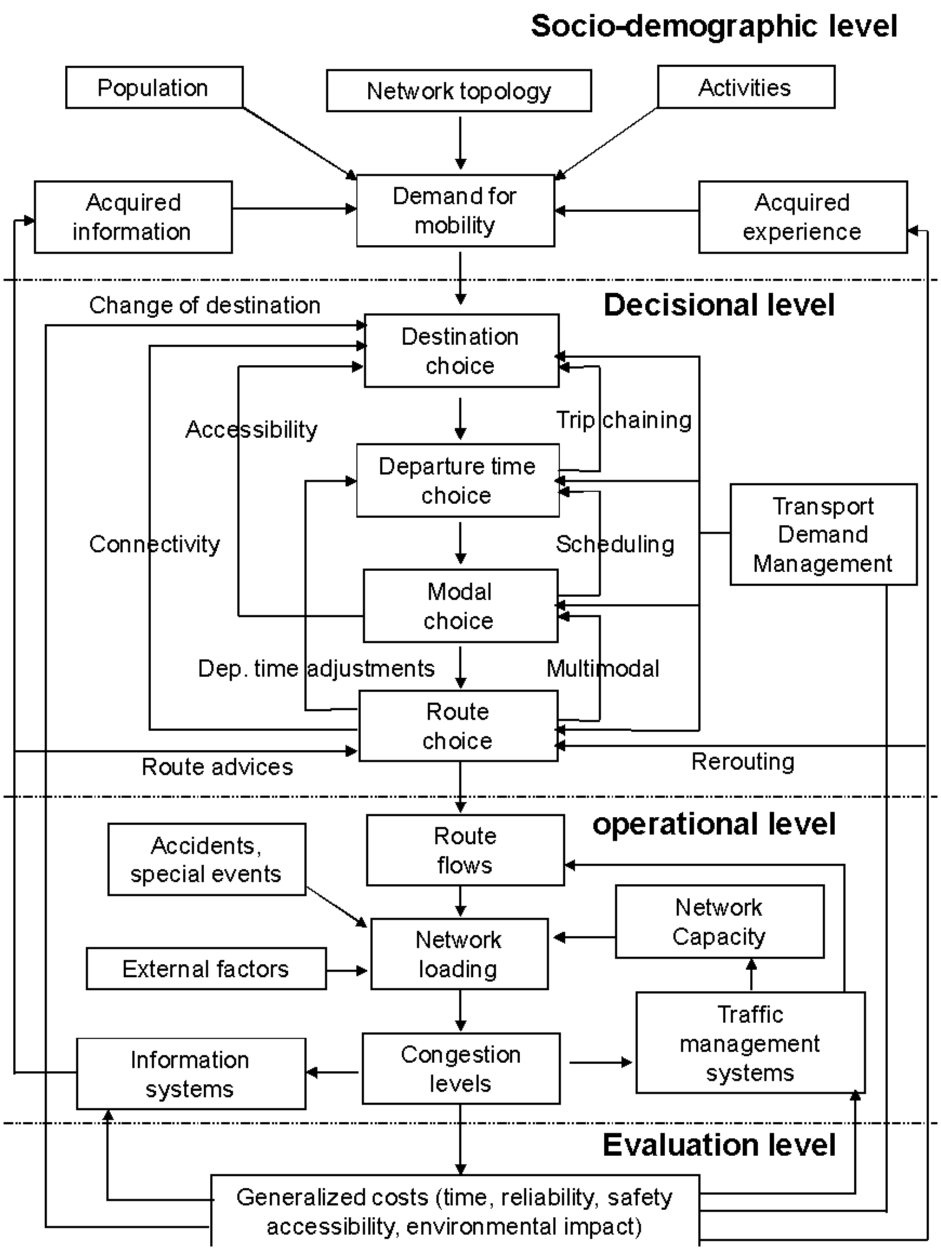

Figure 2: Transportation system structure and model components

The open character of the transportation system shows by the fact that some blocks in Figure 2 that are considered input to the transportation system can actually be elaborated into full models as well. For instance, the population and its activities could be modeled as a synthetic population of agents who make many decisions on which activities to perform, where to live and do activities, which vehicles of transport service subscriptions to own etcetera. Likewise, the transportation network topology (consisting of physical infrastructure like: roads, sidewalks, bicycle paths; but also of service network topology like: public transport lines and time tables, ridehailing service zones, carsharing stations) is assumed to be given. But it can also be modeled with a digital twin representing city authorities (setting regulations, developing infrastructure,…), public or private transportation service agencies and so on.

3.4 Scope and resolution levels in traffic-centered urban digital twins

The schematic representation of Figure 2 is general. Depending on the socio-demographic level of interest, and on the evaluations that the analyst is interested in, the models providing insight into transportation can differ substantially. One could for instance distinguish the decision level into multiple decisions related to different types of activities for which the decision making may differ (e.g. traditional transport models distinguish between purpose of the trip like home-work, home-school, leisure or social activities, commercial trips). Likewise, the operational level is in reality multi-layered and might distinguish operations on various infrastructural levels like the road network, rail network, underground network, airspace, pedestrian or cycling infrastructure, some of which may be partly separated, partly shared spaces.

On top of that, Table 1 lists some additional dimensions along which transportation analyses can be categorized. It shows that scope and resolution level are usually connected. The spatial scope defines the spatial extent of the region that is modeled. Like Figure 3 shows, the more local the interest, the smaller the zone of influence and the higher the level of detail of the spatial units (discrete building/POI (point of interest), borough, municipality, region, province, country) and traffic units (discrete agent, discrete vehicle, distributions of vehicular states, expectation values (also: continuum approximation) of the vehicular flow, zonal averages of vehicular flow). It is obvious that radically different transport models are required for an investigation in the short-term impact (e.g. next week) of a local deviation in a residential neighborhood, versus a 10-year impact assessment of a road charging scheme on the lower income groups in a metropolitan region. Not only will the data requirement (resolution/aggregation level) differ substantially, also the behavior affecting the evaluation criteria of interest differs significantly. This may range from coarse, aggregate regressions of how a population shifts between travel options to stochastic simulation of detailed individual decision-making models of discrete travelers.

One needs to be aware that accuracy of transportation models cannot be infinitely be increased by refining the resolution level. These are, in fact, different things that are often confused. A high resolution level means that the description of the processes allows recognizing more details (e.g. individual vehicles or even passengers inside vehicles, called 'agents') – this does not guarantee, however, that these details are all valid. In many cases, agent-based simulations are valid on the level of distributions (i.e. their average and covariances may be valid, not so the individual samples) and are often calibrated against the same aggregate data as continuous-flow approaches.

So, it is important to realize that, as user needs may be focused on individual streets and local districts, flows may be so thin that a discrete approach feels natural. While simulators exist with a resolution onto that level (whether using discrete or continuous data aggregation), the behavior driving such local decisions can only be described in stochastic terms (e.g. as expectation values, either of multiple simulations of discrete agents, or directly as continuous variables). Inevitably, however, the accuracy (or more precisely: the validity) of more aggregate variables will always be higher than of local, more disaggregated variables.

In other words, no matter the resolution at which the simulation is described, it will always be more valid in describing arterials and motorways that collect large flows, as compared to local streets where the prediction of subtle local influences will always remain problematic and data-driven approaches with detailed local data may be superior.

Table 1: dimensions for transport analyses

Dimension	Category	Example

space	scope	terminal, city block, city, metropolitan area, region, country, continent, world
	resolution	single building, neighborhood, municipality
time	scope	historical, real-time, short-term forecast, long-term scenario forecast
	resolution	seconds, minutes, hours, peak/off-peak, day, month, year
population	resolution	individual agents, households, socio-demographic segments (e.g. income percentiles, age groups), population
activity space	purpose	social, leisure, home-work, home-school, professional, freight

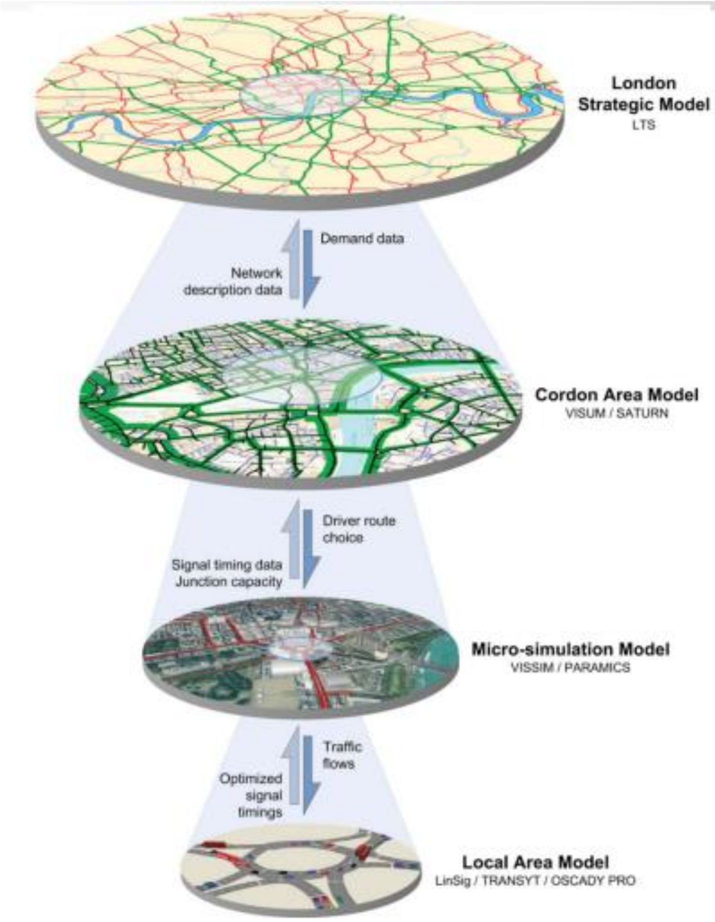

Figure 3: spatial scope and aggregation levels in traditional traffic models[3]

Traditionally, specific instances of the wide range of potential transportation models have been developed – and in many cases fine-tuned over years or even decades – by specific stakeholders in the domain (e.g.: departments of transport, transit agencies). Figure 3 shows some levels and commercial software names that exist on those levels. Related to the spatial scope and level of detail is also the temporal level of detail. A national transportation authority would develop and maintain region- or even nation-wide strategic models for average traffic loads during peak periods in all transportation modes and infrastructures in their jurisdiction, albeit on a rather coarse resolution of municipalities or other aggregate zones (e.g. corresponding

[3] Smith, J., Blewitt, R. (2010). Traffic Modelling Guidelines. Transport for London

to statistical sectors in public databases). Such models support, for instance, scenario and cost-benefit analyses related to large infrastructure projects or tax scenarios. Local traffic controllers would develop detailed second-to-second local microsimulation models of traffic operations on a signalized corridor that they are operating. They may explore what-if scenarios for better incident response (e.g. prioritize emergency services), or real-time optimization of delays for different traffic types.

In a digital twin environment, the ambition is to have a digital replica of the relevant real-world objects and aspects, in the case of DUET centered around the transportation system and its direct impacts (noise, pollution). The use cases and precise positioning along the dimensions of Table 1 were undetermined before the start of DUET (proposal phase) and hence, it was anticipated which traffic models and traffic impact models might be required in a first version of an urban digital twin (D3.3). As the pilot cases and user needs/epics were specified in interviews and workshops with future users of the digital twin platform (D2.2 and D2.3), traffic models already available in the consortium were – to the extent possible – adapted to these emerging needs (section 4.3.1). In future work, as more data comes available and more stakeholders embrace the use of the digital twin for supporting their decision making or communication of plans towards the broader public, further adaptation, expansion and inclusion of other smart city domains (whether or not in transport) will need to be added. Eventually and to serve the different needs of the urban digital twin users, a library of various traffic and Smart City domain models will need to be developed and integrated in the DUET platform on the long run, including a full ontology and tools to convert between different aggregation levels of time, space, population,… Moreover, these models should be compatible and consistent, e.g. finer-resolution models (along all dimensions of Table 1) should be disaggregates of lower-resolution versions and vice versa (section 5).

3.5 Synchronization of an urban digital twin

Since a digital twin is a parallel version of a part of the real world, it needs synchronization with how that world evolves. The models connect to the real world through data in a process called data-assimilation or calibration. Focusing now on traffic-centered digital twins (but can be generalized), an important design issue is how synchronized the digital twin should be and how that calibration is obtained (externally or internally).
The first issue is one of *time scales*.

- real-time / short-term prediction
  Traffic evolves from second to second; for applications such as traffic information or real-time traffic control, the digital twin would have to track reality on the scale of seconds or minutes. For this type of use case, predictions are relevant over a horizon of the next few minutes up to one hour; known as short-term traffic prediction. Data-driven[4] or model-driven[5] predictions and data-assimilations[6] have been proposed for such real-time decision support.

- day-to-day / next-day prediction

[4] Yuan, H., Li, G., 2021. A Survey of Traffic Prediction: from Spatio-Temporal Data to Intelligent Transportation. Data Sci. Eng. 6, 63–85. https://doi.org/10.1007/s41019-020-00151-z

[5] Gentile, G., Meschini, L., 2011. Using dynamic assignment models for real-time traffic forecast on large urban networks, in: Proceedings of the Second International Conference on Models and Technologies for Intelligent Transportation Systems, Leuven, Belgium. Presented at the MT-ITS, Leuven, Belgium.

[6] Tampere, C.M.J., Immers, L.H., 2007. An Extended Kalman Filter Application for Traffic State Estimation Using CTM with Implicit Mode Switching and Dynamic Parameters, IEEE Intelligent Transportation Systems Conference, 2007. ITSC 2007, pp. 209–216. https://doi.org/10.1109/ITSC.2007.4357755

Because of the daily rhythm in traffic, both travelers and traffic or transport system operators have daily strategies that may be updated after every experience. For example, traffic management around a work-zone may need daily fine-tuning, or the management of electric charging networks may require daily predictions of electricity demand by traffic. A digital twin supporting such use cases should synchronize daily to evaluate the latest experience, and predict conditions for the next day or days. Data-driven approaches are dominant in this domain[7].

- slow-moving changes
  On a scale of months/years, both the structural demand pattern, the transportation services, and transport infrastructures will evolve slowly. Even if a digital twin would only be used to predict over years or even decades the impact of what-if scenarios on a strategic level (i.e. which does not require daily nor real-time updating), any traffic model configured for a base year would soon be outdated, if it is not synchronized with living data reflecting the slow-moving changes in demand and infrastructure. Note that this problem resembles the challenge of initially setting up such strategic model. Whereas in consulting, it was custom to adopt an existing traffic model of the region of interest and apply manual changes to update it to a new base year, deployment of strategic traffic models in a digital twin requires the model set-up and updating to be structurally connected to permanently updated, 'living' data sources like geographical databases of infrastructure, timetables, points-of-interest, land-use databases, population statistics, regional economic databases etcetera. See also section 4.3.4.

The second issue of the calibration *method* is a complicated one. No matter the data quality of data used for setting up and initially configuring a model, engineers have always experienced mismatch of model predictions if no specific calibration of model parameters was first performed. Calibration refers to a wide variety of automated, semi-automated and – very often – manual manipulations of parameters in an attempt to validly reproduce model outputs of a known reference case, and to validly predict changes to this reference case (actually, some refer to the former as *calibration* and the latter as *validation* of the model). The more complicated the model (e.g. higher dimensionality of input parameter space, higher non-linearity and/or non-convexity of the model's transformation of inputs into outputs and into a calibration objective function), the less successful automated calibration gets and expert intervention is inevitable. As a result of this manual calibration being tedious and time-consuming, usually the model is only calibrated against one data sample (e.g. a so-called "representative" day), which may not represent the central case. Moreover, methods that proved successful in one case, may transfer badly to new cases because the characteristics of the network (traffic patterns, level of congestion) may differ strongly; and even more so: the combination of data available to perform the calibration (almost without exception an underdetermined problem, i.e. for which insufficient data exists to unambiguously define 'optimal' parameters) is usually unique for every case. As a result, there is a need to include systematically in a digital twin environment comparable data sources for each city or region to which models need to be configured, and to provide automated calibration support. However, given the state of the art in automated calibration, only the former (make available data in uniform formats) seems feasible in the early stages of urban digital twin development (see section 4.3.3).

[7] Ma, D., Song, X., Li, P., 2021. Daily Traffic Flow Forecasting Through a Contextual Convolutional Recurrent Neural Network Modeling Inter- and Intra-Day Traffic Patterns. IEEE Trans. Intell. Transp. Syst. 22, 2627–2636. https://doi.org/10.1109/TITS.2020.2973279

4 SC Domains and models and their integration within DUET

4.1 Initial status of domain models and their integration before DUET

DUET explored a first integration of traffic and traffic-related impact models. The aim was that some basic modeling data and functionality would be available covering a large territory. The basic modeling functionality is thus on a rather high spatial aggregation level (e.g. municipality level) and low time resolution (e.g. stationary state in peak and off-peak periods). The explanatory character of this basic layer, which can be auto-configured (section 4.3.3), is rather crude, only capturing basic transportation relations between production and attraction of activities and trips in aggregate zones. More refined models allow zooming in on city regions (diameter ~10-20km) within the larger territory, see section 4.1.1. The modeling principles at this level are comparable to the basic modeling layer, but the principles have been applied on data with smaller spatial aggregates and (for the time being, exogenous to the DUET platform) calibration has been performed to produce valid average (stationary) flows. Like the basic modeling layer, such calibrated regional models can be of the type Static Traffic Assignment (sections 4.1.1.1 & 4.1.1.3) or at the finer time resolution of dynamic traffic assignment (4.1.1.2), which considers peak hour dynamics with queues building up and dissolving. Both models capture structural flows and routing interaction with queues, but does not provide fine details e.g. no local streets, no tracking of local queues at individual intersections along arterials, nor of local routing towards parking spaces. Finally, the digital twin allows zooming in on local neighborhoods in city districts, where in principle every individual street and intersection is considered. Obviously, the validity and accuracy here strongly depends on the availability of detailed local data as the CityFlows model is a pure descriptive model fusing data and no scenario-model for extrapolations to future scenarios (see section 4.1.1.6).

For traffic-related impacts, one emissions model and two noise models were integrated in DUET (see sections 4.1.1.4 and 4.1.1.5).

All these models initially had their own ontology of entities and properties, in their own data structures (so even similar objects in different models could be in different formats and not trivial to match). Hence, before DUET it was impossible to run different models on the same city network, or to connect chains of traffic models and impact models without prior development of a tailored export/import interface or database link.

4.1.1 The DUET models

The domain models available in DUET have been described in D3.3. In this section and only if required, we complement that information, notably when model description in D3.3 was incomplete or other models that were available to the partners have been integrated after completion of D3.3. Updates, modifications, and new model developments that were developed specifically for the purpose of DUET integration are discussed further in section 4.3.1.

4.1.1.1 Static traffic models (KUL)

In the first version of this deliverable, D3.3, no static traffic models of KUL had been described. Nevertheless, KUL disposed of various implementations of static traffic assignment algorithms used as educational and research tools[8]: deterministic equilibration algorithms like MSA, FW, TAPAS, Dial-B, and stochastic equilibration algorithms like MSA, Dial, and recursive logit. There was, however, no ambition to integrate any of these into DUET as P4All already disposed of an integrated multimodal STA with API interfaces for integration into cloud-platforms.

Some STA algorithms of KUL, however, have been integrated with dynamic traffic assignment (DTA) algorithms into the Dyntapy software, and are therefore available as additional models within DUET (section 4.3.1.1). The reason of this inclusion is that the integration of KUL's DTA models into DUET required a redesign of the DTA code (including a re-engineering from Matlab into newly developed Python code); an occasion that has been exploited to develop common data formats and modeling scripts for most KUL's STA and DTA combined. Another reason is that configuring a valid DTA for DUET cannot be done without, in the process, first building a less detailed and more easily configurable STA of the same network and verifying whether this yields valid stationary traffic outputs. It is, thus, a relatively small effort to also make the intermediate STA that was used to set up and run the DTA on the same network and zoning also available for computation within DUET.

4.1.1.2 LTM dynamic traffic assignment model (KUL)

The Link Transmission Model (LTM)[9] is a macroscopic dynamic traffic assignment (DTA) model developed at KUL. It considers time-dependent demand between origin and destination zones and propagates it over the network according to a kinematic wave model and 1st order node models. By doing so, it considers congestion build-up and dissipation, as well as spillback of queues. It is assumed that drivers choose the fastest path depending on their departure time and the delays due to congestion experienced along their trip (dynamic user equilibrium). For the time being, no taste heterogeneity is assumed in the assessment of what is the fastest route (so-called: deterministic user equilibrium); LTM version with heterogeneous perception of cost is being developed and will be available in DUET once it is ready and fully tested.

For more info about this model, see section 3.1.2 of D3.3 and 4.2.3 in D4.3.

4.1.1.3 Traffic Modeller static traffic model (P4All)

This model[10] was developed in another EU-project[11] and was described in Annex 6.1 of D3.3. It has been integrated into the DUET platform through a dedicated API and model agent (see D3.9). The static assignment algorithm has been parallelized for fast computations in a digital twin environment[12].

4.1.1.4 NoiseModelling (P4All)

NoiseModelling is a library capable of producing noise maps of cities. This tool is almost compliant with the CNOSSOS-EU standard method for the noise emission (only road traffic) and noise propagation. It can be freely used either for research and education, as well as by experts in a professional use. The model is described online[13] and in the scientific literature[14].

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[8] https://gitlab.kuleuven.be/ITSCreaLab/public-toolboxes/matlabtraffictoolbox

[9] Himpe, W., 2016. Integrated Algorithms For Repeated Dynamic Traffic Assignments: The Iterative Link Transmission Model With Equilibrium Assignment Procedure (Dissertation thesis). KU Leuven, Leuven, Belgium.

[10] https://trafficmodeller.com/

[11] Jedlička, K., Beran, D., Martolos, J., Kolovský, F., Kepka, M., Mildorf, T., Sháněl, J., 2020. Traffic modelling for the smart city of Pilsen, in: 8ICCGIS. Presented at the 8th International Conference on Cartography and GIS, Bulgarian Cartographic Association, Nessebar, Bulgaria.

[12] Potuzak, T., Kolovsky, F., 2021. Parallelization of the B static traffic assignment algorithm. Ain Shams Engineering Journal. https://doi.org/10.1016/j.asej.2021.09.003

[13] https://noisemodelling.readthedocs.io/en/latest/#

[14] Erwan Bocher, Gwenaël Guillaume, Judicaël Picaut, Gwendall Petit, Nicolas Fortin. NoiseModelling: An Open Source GIS Based Tool to Produce Environmental Noise Maps. ISPRS International Journal of Geo-Information, MDPI, 2019, 8 (3), pp.130. ⟨10.3390/ijgi8030130⟩. ⟨hal-02057736⟩

4.1.1.5 Urban Strategy air quality and noise models (TNO)

The TNO Urban Strategy air quality model calculates the NO_2 and PM_{10} concentration emitted by traffic. It uses the Dutch SRM1 and SRM2 (Standaard RekenMethode / standardized calculation methods) as described in the RBL 2007 (Dutch regulation for air quality). The Urban Strategy Noise Module focuses on the generation of Noise maps and delivers the output on which noise-exposure distributions can be derived. In the Netherlands it is also used as a policy making tool, in order to see the effect of different planning scenarios for infrastructure, buildings and sound barriers.

For further description of these models, see sections 3.2.1 and 3.3.2 of [D3.3](D3.3)

4.1.1.6 CityFlows local traffic model (IMEC)

Summary

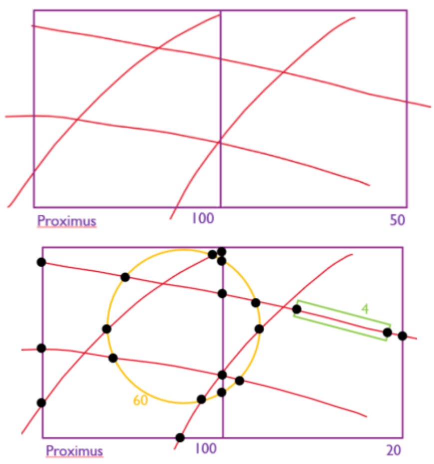
Cityflows focuses on supporting mobility experts in interpreting homogeneous mobility data sources. Based on different mobility data sources (i.e. telco signalling data, wifi scanning data, ANPR camera data, Telraam data, counting loops, speed radar data, bike sharing data, etc.) the model distributes a unified density of traffic and discriminates between different modalities, such as bikes, pedestrians and non-motorized traffic, in the streets of a certain area. This unified unit (i.e. density) enables the mobility experts to compare multimodal traffic business in time and geography. Next to this the model provides a accuracy score, which enables the mobility expert in knowing when to trust the output data and when not.

Inputs

The CityFlows model requires data sources to feed to its model. These can be divided into 2 classes:

- **City infrastructure:** The data on the infrastructure of the city should - as a minimum - provide a street grid in a graph-like structure, preferably in WGS84 format. Street segments and their connecting intersections are essential. Statistics about demography, population density, can all be useful information to enrich the model.

  General crowd counts: This includes any data that gives a sense of the amount of people in a certain area at a certain time. See figure A.
- **Mobility counts:** A typical data source contains the following key attributes:
  - Type of data source: according to the way data is exposed, counts can be snapshot-like, cumulative with unique counts, cumulative with non-unique counts, or point-measurements.
  - Area covered by the source or sensor: For cameras: this can be the viewing angle and reach, for telecom providers it can be the Voronoi grid of a triangulated signal, for a telraam it can be the street segment covered by it, etc.
  - Time interval: especially for cumulative counts, the interval of the aggregation should be available in the metadata.
  - Modality information (optional): if data specifically measures one or more modalities: cars, bikes, pedestrians.
  - Counts: the actual payload of the data.
  - Direction (optional): a direction (if known) of counts in a street can be given.



Model summary steps

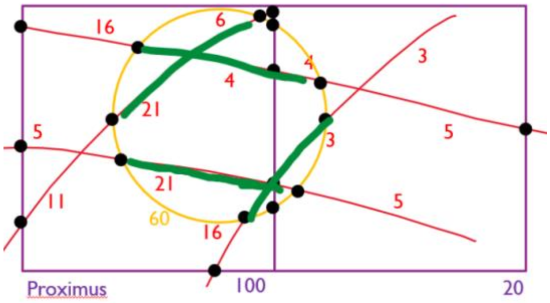
Step 1: Street Cutting

The street cutting is a process where the geolocation metadata of all the data sources is used to divide the given street grid in a finer mesh. The result is a street grid where each segment knows which data points are applicable on it.

Step 2: Transformation of data source types

Data sources of cumulative data types are transformed to the same, directly comparable format. We aim to use data standards such as NGSIv2 as much as possible.

Step 3: Fusion and flow calculation



The data sources are fed as constraints to the cityflows model. The model takes all metadata as constraints into account and calculates a density of people in the street segments. The steps are linked between timesteps.

Requirement parameters are the total estimated number of road users, the number of users on a road segment in the previous time interval, the number of people entering an intersection and leaving it towards another street segment (i.e., continuity constraint). The idea is that for each time interval the total number of people should be distributed over the street segment grid taking into account these constraints. See figure C.

In order to deal with data insufficiency, the gaps are filled in as follows:

- the model takes statistics (for example global split) into account by enforcing that on a global setting the modal split must be 70/30 for example. If local or even dynamic modal split data is available, this can be used.
- in case there is few data, the main model distributes the data from the available data point evenly along the streets, possibly taking into account features such as street with, road width, etc.
- if there is more data, this serves to apply local corrections to the distribution proposed by the model in step 2
- If there is no data source for a certain point, either data can be estimated from in- / outflows of other cells, or no calculation can be done whatsoever.

Outputs

The output of the algorithm consists of a data set giving densities, for every street segment of the given grid (provided that there is data covering it), split up between the different modalities available from the data sources, see Figure 4.

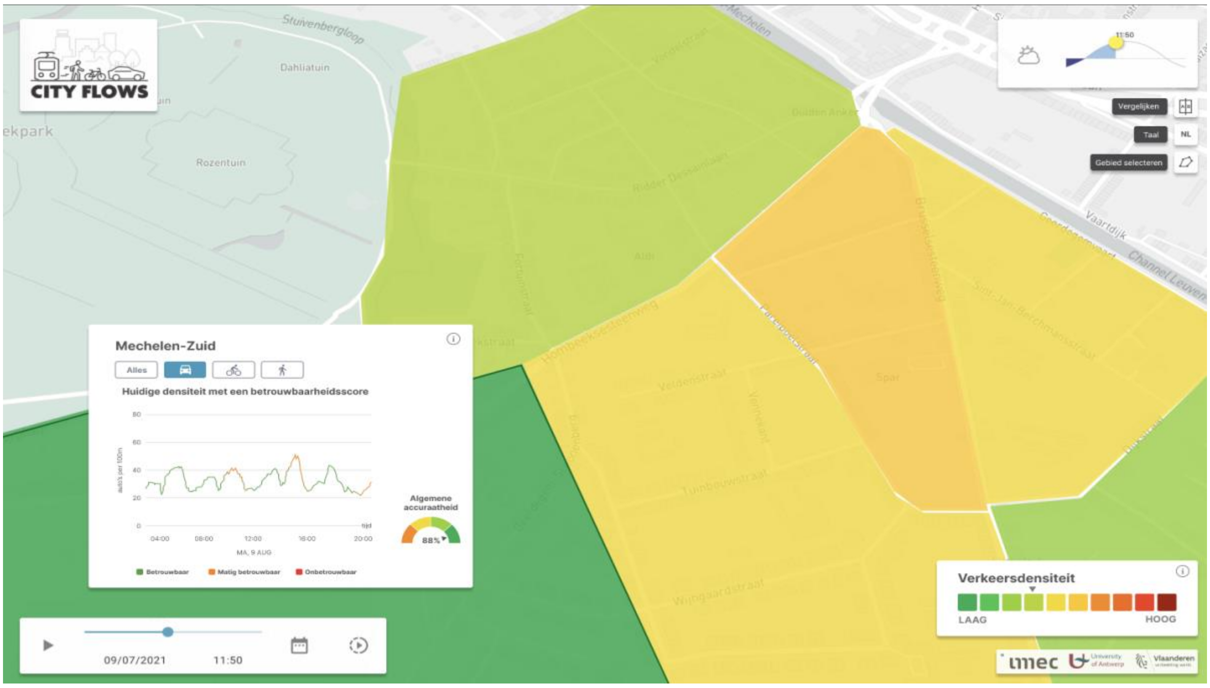


Figure 4: A sample output visualisation (at neighborhood level) mockup

Understanding traffic models and determine optimal sensor placement

The Cityflows model allows to

- compare with averages/ predictions from the traffic assignment models
- understand where additional sensors may be necessary
- reveal that at some locations additional sensors are pointless as they are already sufficiently described by near-by sensors and the constraints they impose.

4.2 Ambitions and scope of DUET

Summarizing the properties of the model set that was available for integration in DUET (section 4.1.1), it appears from Table 2 that the traffic models focus largely on the regional level (= the inner city + the surrounding land and satellite municipalities from which the majority of commute traffic is attracted) and on the strategic time horizon. Moreover, most traffic models available are oriented towards motorized road traffic (with no explicit behavioural models for freight or logistics, hence labeled in the Table as "car" traffic, where trucks are converted into person car equivalents). An exception is the CityFlows model that has a more local scope (inner city districts) and covers, apart from cars, also bicycles and pedestrians; however, this model is purely descriptive, i.e.: it estimates the current state from available data but does not support what-if scenario extrapolation.

The traffic impact models capture exhaust gas and noise emissions by motorized traffic on a local scale and over a broad spatial scope ranging from districts to entire regions; their time resolution is coarse (annual and daily profiles) corresponding to the needs of strategic planning.

Table 2: properties of the models available in DUET

	spatial scope	time horizon	transport mode	Air quality impact	Noise impact

Static unimodal assignment model KUL	regional (inner city + satellites)	strategic planning	car		
Static multimodal assignment model P4A	regional (inner city + satellites)	strategic planning	car, PT		
Dynamic traffic assignment model KUL	regional (inner city + satellites)	tactical and strategic planning	car		
CityFlows Local traffic model Imec	inner city districts	current state estimation	car, cycle, walk		
Urban Strategy Air quality and Noise model TNO	inner city or regional (inner city + satellites)	strategic planning	car	yes	yes
ATMO Air quality model VITO	regional (inner city + satellites)	strategic planning	car	yes	
NoiseModelling P4A	inner city	strategic planning	car		yes

It is interesting to compare these properties of the available models to the user needs (epics and user stories) resulting from the stakeholder consultation that was reported in deliverables D2.2 and D2.3 of DUET. Table 3 selected from those deliverables some traffic-centered stories that users would like to address using urban digital twins. Almost without exception, they are strategic planning problems. Many, however, zoom in on a more local inner-city scale than most of the available traffic models of Table 2 do. Moreover, while these traffic models focus on car traffic only, many user stories involve, in addition to car, public transport and/or active travel models like cycling and walking (and related personal micromobility solutions like scooters). The traffic impact models match very well the scope, time horizon and impacts that users expressed interest in.
We conclude that the match between the available traffic models in DUET and the user needs revealed by DUET is still partial: while impact models need little modification and indeed users see added value in the integrated consultation of (multiple) traffic models and traffic impact models, for some user stories, the scope of traffic models should evolve towards a higher level of detail (more local scope), and towards inclusion of alternative modes to car travel. This should ideally include parking, modal shift and multimodal trip making decisions by the population (urban + visitors & commuters). We elaborate on these needs beyond DUET in section 5.1.

Table 3: summary of user story types collected from the D2.2 and D2.3 interviews with stakeholders

epic/user story	spatial scope	time horizon	transport mode	Air quality impact	Noise impact

controlled parking / promote use of public transport	regional (inner city + satellites)	daily + strategic planning	car, PT		
stimulating combined use of car, PT and active modes	regional (inner city + satellites)	strategic planning	car, PT, cycle, walk		
green routes to reduce pollution	regional (inner city + satellites)	strategic planning	car	yes	
parking management application	inner city districts	daily management	car		
analyse trends in noise levels	inner city districts	strategic planning	car		yes
analyze trends in air pollution levels	inner city districts	strategic planning	car	yes	
insights in mobility flows at neighborhood level	inner city districts	strategic planning	car, PT, cycle, walk		
impact of LEZ on mobility and air pollution	inner city districts	strategic planning	car	yes	
healthy and safe routes for vulnerable road users	inner city districts	strategic planning	cycle, walk	yes	
impact of new buildings and activities	regional (inner city + satellites)	strategic planning	car (PT, cycle, walk)		
match demand and supply of public space	inner city districts	strategic planning	car, PT, cycle, walk	yes	yes

4.3 Achievements of DUET model interaction

The models described in the previous sections had been developed before DUET, some as part of an integrated framework (UrbanStrategy), others as a webservice (Traffic Modeller, CityFlows), open-source toolkit (NoiseModelling), or as research or educational toolkit (KUL static and LTM). Integrated analyses or analysis of the same case with different traffic models was impossible (without dedicated manual conversion and re-configuration). DUET D4.3 discussed the integrated implementation of these models in an effective chain of models using an architecture built around the Message Broker in the DUET core. This required progress regarding the implementation of the section 4.1.1 models as described in D4.3, as well as the message schemes defined to enable the model-to-model connections.

This section describes modifications to some of the models of section 4.1.1 that were needed for this integration.

4.3.1 Enhancements to the interacting models

4.3.1.1 KUL: Dyntapy: integrated static and dynamic traffic assignment and demand generation

Providing traffic models for an urban digital twin entails 4 specific challenges:

a. to set up and configure the traffic model for any study area of interest;
b. to integrate various traffic models of different spatio-temporal resolution and scope in a consistent way;
c. to integrate traffic models with other domain models;
d. to calibrate the model's parameters such that its predictions are valid.

Dyntapy[15] is a traffic modeling toolkit developed at KUL that is conceived to be integrated into the DUET platform and that addresses all challenges mentioned above; although all are to some extent work in progress. It is described in Annex A.

Challenge a: configuring traffic models for any area of interest

Dyntapy configures a road traffic models for a given study area using living data sources, in casu OpenStreetMap (OSM). Not only can any network be extracted and converted into a connected routable graph, it also offers a demand-generation model (Poidpy, see section 4.3.3 and annex B) that creates an origin-destination (OD) matrix for any desired zoning, and it automatically connects the zone centroids (i.e. its gravity center) to the physical road network. At the time of writing, additional modules are being developed for aggregating demand and network data for the influence zone around the study area, such that traffic exchanged with that influence area or crossing through the study area can be modelled without the need for a full level-of-detail modeling of these peripheral zones.

Challenge b: consistently integrate different spatio-temporal resolutions

All traffic models within DUET are macroscopic or continuous flow models, which disregard the discrete vehicles or travelers and describe traffic in terms of aggregate/continuous variables such as flow and density. Dyntapy aims to bridge between various spatio-temporal resolutions of traffic models withing DUET (at KUL or other DUET-partners). In terms of spatial resolution, the range is from districts and individual streets (CityFlows, section 4.1.1.6) to urban regions covering the inner city and its satellite towns that consider aggregate traffic zones (P4All traffic model, section 4.1.1.3; Dyntapy). In terms of temporal resolution, Cityflows considers minute-to-minute fine dynamic traffic states, the dynamic traffic assignment (DTA) of Dyntapy coarse dynamics of peak periods (e.g. in 10-min steps), and the static traffic assignment (STA) of Dyntapy and of P4All further aggregates to stationary averaged peak periods.

The data structures inside Dyntapy have been defined such that the STA and DTA are maximally compatible. Whereas they both operate with traffic analysis zones, the concept of centroids can be converted into an intra-zonal assignment. Indeed, the concept of centroids connected to one or a few nodes in the zone leads to an unrealistic local concentration of traffic around those connecting nodes. This is incompatible with the local fine-grained resolution that is required for many inner-city use cases (see section 4.2) and that is also considered in CityFlows. Dyntapy's intrazonal assignment considers the access points to the zone as potential origins or destinations and then distributes flows from and to these access points over the POIs in the zones. The current method is a rather pragmatic intrazonal traffic assignment; however, it prepares the zone-based STA and DTA for inclusion of finer intrazonal traffic simulations that may include for instance local parking search or data-driven local distribution of traffic extracted from, for instance, CityFlows.

Challenge c: integration with other domain models

[15] https://gitlab.kuleuven.be/ITSCreaLab/public-toolboxes/dyntapy

A Dyntapy model client was developed allowing to pack Dyntapy models to run as a Docker container (see D4.3).

Challenge d: calibration of model parameters

Within DUET, no specific calibration modules or support is being developed.

4.3.2 Interaction of DUET models

DUET deliverable D3.5 "Cloud design for model calibration and simulation" describes how models interact. The DUET system contains multiple models to perform the calculations for the Digital Twin. The DUET T-cell architecture enables the integration of these models of the DUET system. Computational models (air, noise, traffic) are integrated in DUET by connecting to the DUET T-Cell by means of a suitable API.

This API enables the models to be controlled by the DUET system. The API facilitates the start and stop of the simulation, calibration and validation, the exchange of necessary data and results. The API is accessible using a gateway to the Apache Kafka Platform, and relays messages between Kafka and the models. Kafka functions as the main message streaming platform in the DUET T-Cell architecture.

The availability of the individual models is realized using Docker containers. The individual models have been packaged inside a Docker container enabling deployment anywhere in the available cloud, thus forming a cloud of available models. The models run outside the DUET T-Cell and are interconnected using the API. A Docker Orchestrator has been implemented for starting up, retrieving status and termination of the individual model docker containers.

See for more technical details on this integration D3.5. See for a discussion on further integration of domain models section 5.1.2.

4.3.3 Interaction of DUET models and data: towards automated model configuration

Configuring domain models for a specific case on which one likes to analyze scenarios is no trivial task. We confine ourselves here to the domain of traffic modeling, but similar considerations hold for all domain models. Configuration is the process of setting up the model's input parameters for a given region of interest, say a city and its surrounding influence area. Setting up means that the entities and their properties relevant for traffic modeling in that region of interest need to be identified and quantified. Traffic models typically split their total entity set in supply and demand entities. Supply entails the road network, intersections and all relevant infrastructure and controls that determine how traffic propagates in the network.

The supply side of traffic and its physical infrastructure are the layer of entities that is most developed in DUET so far: entities like 3D buildings, streets, squares etcetera have been the first to be defined in DUET's ontology and are used for validation and as input to the domain models for traffic and emission and noise propagation. DUET integrates generic data sources of the physical entities and infrastructures like OpenStreetMap and OpenTransportNet. Setting up supply for a regional traffic model requires selection of relevant entities from these sources that belong to the modelled region, and selection of relevant properties. Some conversion of generic properties and extraction of complementary properties is required. For instance, link properties like capacity and travel time function parameters should be configured based on generically available properties like number of lanes, road type, speed limit etcetera. Moreover, it may be desired to omit certain links (e.g. minor roads in the periphery of the studies region) or aggregate them to larger connections. Dyntapy configures the supply side traffic network with all properties required for traffic modeling from

OpenStreetMap (OSM). Moreover, while doing so, it adds virtual entities called connectors to connect this physical network to the demand data that is defined on the aggregate level of traffic analysis zones (see Annex A).

For the demand side, no direct generic data sources are available in DUET. Since demand is no collection of physical entities but rather a result of socio-economic activities, it cannot so easily be cast in maps and databases like it was the case for supply. Traditionally, demand data is inferred from two main complementary data types: land use data and behavioral surveys. Like Figure 2 showed, trips are the result of people connecting activities at different locations. Activity locations or points of interest (POI) thus reveal where trip ends (origins or destinations) should be. How these trip ends are connected with activities, by whom and how frequently, can be inferred from data revealing people’s trip-making behavior; traditionally through mobility surveys and increasingly through passive tracking of a population sample on the aggregate (e.g. telco cell-handover data) or disaggregate level (e.g., life tracking apps, telco customer records). See for use of the latter data to infer origin-destination (OD) data developments in the H2020 project MOMENTUM[16]. Within DUET, a module has been developed (though not integrated in the platform) that automatically estimates OD-trip matrices from the POI data in OSM. Given a layer of traffic analysis zones, the tool quantifies for each zone the number of POIs in OSM classified in relevant POI classes like residential, shops, offices, services etcetera. Each POI-type produces or attracts an average number of trips in the analysis period of interest, that are connected by a distribution tool that takes into account the connection quality between the production (origin) and attraction (destination) zones. This quality is derived by connecting the zones by virtual connectors to the traffic network and measuring the travel time between them. The tool is explained and showcased in Annex B.

4.3.4 Easy integration of future improvements to DUET models

While the current status of DUET’s domain models may not address all user needs (see discussion in the next chapter), these models are permanently being updated and further developed, both inside DUET and in other projects. Through the existing DUET API’s, updated models can directly be made available to DUET users (as long as the update does not affect the validity of the existing API).

This is a major step forward as it makes DUET a platform with living models built on living data sources, herewith alleviating significantly the need for constant model updating.

[16] MOMENTUM consortium, 2020. MOMENTUM Deliverable 3.3: Methodologies and Algorithms for Mobility Data Analysis.

5 Beyond DUET: some reflections on future development of urban Digital Twins

5.1 Digital Twin user needs beyond DUET

The domain models of DUET are all indispensable for the epics and user stories that different users defined in D2.2 and D2.3. However, while they are necessary, they are not sufficient to address all needs of the users. On the one hand, they express needs that require further refinement and/or development of the available domain models (that are all linked to mobility and its impact); we discuss those in section 5.1.1. On the other hand, some epics require models of complementary Smart City domains to be integrated in DUET; we discuss those in section 5.1.2.

5.1.1 Development directions of domain models already integrated in DUET: mobility, traffic & traffic impact

The DUET traffic models play a central role in addressing the user needs. Still, they bear the legacy of a development history that was focused on regional, strategic policy that primarily concerned peak periods when pressure on the transportation system was at its maximum. Urban digital twins, however, are targeted to a much wider and more diverse range of stakeholders. As a result, there are needs that have not yet been (fully) addressed by the currently integrated traffic models, for instance:

- finer-grained local traffic impact scenario predictions
    - current models mostly sensitive to strategic/structural mobility measures (like: infrastructure development, urban planning, congestion charging, (multimodal) accessibility), whereas city stakeholders are faced with many local measures too (like: local mobility impact studies of new buildings, parking, fine-grained traffic management, solving local conflicts between motorized and slow traffic, curb management, temporary measures e.g. around schools)
    - as a result, of the already modeled processes, there is a need for finer demand and (re)routing modeling; it also calls for additional components of the mobility, logistics and traffic system to be integrated in the traffic models (see further).
- multi-period models
    - current models focus on peak periods;
    - impact on city (e.g. livability) is often equally or even more important off-peak and in weekends/holidays that are currently not modeled
- extra outputs
    - main outputs of existing traffic models are link flows and average speeds; they are the inputs for the traffic impact models (noise, emissions). Moreover, while the digital twin projects model outputs on the physical world that is presented (even in 3D) in a high resolution and thus, this suggests outputs to also be trustworthy on this level, existing traffic models are based on average relationships, correlations, empirical rules etcetera that are only valid on the aggregate level but get more noise and unreliable on more disaggregate, local level. This distinction cannot be seen by the users.
    - It is recommended that metadata on the outputs be available: how certain are the results, how stable or variable can actual values be expected around their mean? This calls for adding distributional characteristics to the model outputs (i.e. confidence intervals and percentiles). Even though such subtle information might be difficult to interpret by the user (especially the

less expert ones), such distributional data might be exploited by the DUET platform to select which information to present at which level (e.g. while zooming in too closely, remove or gradually blur details having too high variance), which could be an indirect way of making the user aware of the confidence bounds and limited disaggregate validity of model outputs.
    - By only providing link-aggregate outputs, many dimensions and alternative aggregation levels that can be meaningful to users might get lost. It is recommendable for models to expose to DUET additional outputs like: cordon analysis, selected link analysis, watershed analysis, accessibility, access and reachability measures, isochrone maps, route analysis, OD analysis, skim matrices. Currently, however, the limited ontology of DUET does not acknowledge the existence of entities and properties that relate to these outputs (e.g.: demand-related entities like demand zones, cordon, route, route bundle, access tree/bush); hence, no exchange of such outputs is possible for now. Moreover, even when the ontology would already exist and be supported by DUET, some outputs may require changes inside the traffic models themselves. For example, KUL's traffic models use an implicit representation of routes that avoids route enumeration, which is convenient for memory usage but requires explicit reconstructions of the route-based variables whenever any DUET module would be registered to such outputs.

Even more fundamentally, many users express interest in use cases that involve components of the transportation system for which no models are available yet in DUET. Some examples of missing mobility and transport model components:

- parking model
- pedestrian model
- cycling model; other light vehicles
- vehicle fleet model
- mass transit model
- shared-mobility and MaaS (mobility-as-a-service) system models
- microscopic travel demand model (including tour-based correlations, vehicle and mobility tool ownership)
- modal choice and multimodal trip behavioural modeling
- traffic management and control model
- mobility and traffic signposting, and dynamic information provision model
- behavioural models in non-recurrent conditions
    - incidents, accidents, manifestations, events, disasters, evacuation…
- impact models
    - safety
    - social impact
    - fiscal impact

5.1.2 Development directions of domain models not yet integrated in DUET: challenges across multiple Smart City domains

The previous section discussed future development directions for the person-mobility domain. Many user stories express needs beyond that domain into related Smart City domains that are worthwhile considering including in future versions of DUET:

- synthetic population model distinguishing relevant subsections of the population:

  - age groups, socio-economic strata, gender, people with special needs,…
  - activity-based demand model
  - social network and interaction model
  - economic interaction model
  - labor market model
- weather and climate modeling
- city logistics model (including reverse logistics)
- housing market and land-use model
- energy distribution model
- (transport) infrastructure model
- biodiversity model
- governance and policy model
- crime modeling[17].

5.1.3 Ontology for urban digital twins: towards a deeper integration of DUET models and data

All Smart City domain models and data processing procedures that have been integrated in DUET (and will be added in the future) had originally not been conceived for deployment in a data-rich, living digital twin platform where many other data procedures and models coexist. Their systematic integration requires:

- *development of an urban digital twin ontology*:
  An ontology is a formal naming and definition of the types, properties, and interrelationships of the entities that really or fundamentally exist for the Smart City domains of interest (e.g. traffic and transportation).
  Properties of entities are time-dependent: they have unique historical values (retrocasts), estimates of their current values (state estimation), and predictions of their future values (forecasts) under various scenario boundary conditions.

- *rethinking the role of domain models*:
  Essentially, models relate properties of entities to each other, based on theoretical or empirical knowledge that the modeler expressed as analytical, statistical, or procedural relationships. They can set values of certain properties based on registration to other properties present in the ontology. Considered from this perspective, we can distinguish different types of services that models may provide in a digital twin:
  - property transformations: examples are (dis)aggregation over any relevant dimension like: space, time, or population subgroups.
  - estimation/fusion/inference of latent variables: while no direct empirical observation may exist of a latent property of an entity, its value may be inferred from observed data through some form of statistical inference or fusion of multiple heterogeneous data sources; a so-called measurement model then relates the latent, unobservable and so far unknown property to observable properties (data) or to other latent properties that have been inferred before.
  - extrapolation/prediction: when a model relates historical and/or current state estimates to future properties of the entities, forecasts are produced. These are inherently uncertain and

[17] Leitner, M. (Ed.), 2015. Crime Modeling and Mapping Using Geospatial Technologies, 2013th edition. ed. Springer, Dordrecht

subject to assumptions on scenario boundary conditions and to decision variables (some of which may be controlled by the user).

- *exploit the living digital twin context for permanent training of models:*
  As a digital twin is a living representation of reality that permanently acquires updated data, its properties migrate over time from being forecasts to current state to retrocast. During this process, the property evolves from a mere extrapolation, over inferred property conditioned on earlier and current observations, into retrocast conditioned on earlier as well as later observed data. Being conditioned on ever more data, the uncertainty decreases during this process. Hence, the retrocasts can be seen as ex-post ground truth and allow for permanent training or calibration of the state estimation and forecasting models.

Within DUET, parts of an ontology and of the model services have been implemented. However, this exercise should be further complemented and permanently be polished for a smoother and more structural integration of DUET's data and models.

5.2 Broader support of case and scenario management and control

5.2.1 (Semi-)automated set up and calibration of UDT models/cases

Model/case setup

Within DUET, traffic networks can be automatically extracted and set up as part of the Dyntapy traffic modeling toolbox (section A.1); traffic demand OD-matrices can be extracted and set up through the Poidpy toolkit (Annex B). These procedures only configure entities and properties that need to be known for traffic modeling. However, support for a more encompassing and systematic set up of all related modeling entities and their properties, respecting the digital twin ontology proposed in section 5.1.3 and as proposed in D3.9 should be further elaborated and to the extent possible, be automated with minimal human intervention during configuration.

Model calibration

At present, no automated calibration procedures exist, nor do there exist generally applicable guidelines on which data is minimally required to guarantee a certain level of validity of the model outputs. Within DUET, the more refined models will therefore be configurable in principle over the entire territory, but in practice can be trusted empirically only for those zones for which substantial calibration efforts have been performed in the context of specific pilot use cases using dedicated data sources. These calibration efforts, for now, are assumed to be done exogenous to the DUET platform, and specific configurations with calibrated parameters for pilot use cases need to be packed in separate Docker containers.
DUET supports, however, a common description of the network and physical objects (e.g. buildings) with shared properties. This description of the physical world is shared with the data sources that connect to DUET, herewith allowing for a direct comparison between calibration and validation data and the model states computed by DUET's domain-models (traffic and traffic-related impacts noise and emissions) without the inconvenience that used to exist when mapping models and data sources that each had their own data model, indexing, and properties definitions. As such, the DUET platform is ready as an infrastructure to which calibration and validation can conveniently be connected: the calibration/validation module will act as any

other model that subscribes to and publishes properties of the physical world. In this particular case, it would subscribe to model outputs of which corresponding reference data exist, compute adjusted parameter settings based on observed mismatches between model output and data, and publish the adjusted parameters for updating the model being calibrated/validated. This procedure could iteratively improve the model's calibration.

Conclusions will be drawn on the data and calibration requirements for other detailed models, based on the experiences in DUET. The integration and mutually consistent data models of the different domain models and data flows are an important asset for future development of efficient calibration and validation workflows.

5.2.2 enhanced scenario management, optimization, control, and analysis

In D3.9 on data broker specifications and tools, it is concluded that: "as of today there is no semantic description of cases and scenarios, nor is there a schema or standard API for its management. As digital twin technology matures, such a standardization may foster further interoperability between digital twin building blocks." Chapter 2 of that deliverable D3.9 describes definitions of cases and scenarios and how interactions between data, models and scenarios can be set up, managed and orchestrated by the user (in principle). So far, however, this has not all been turned into practice in the beta releases of DUET.

In addition to such implementation, users would benefit from some additional tools to manage, optimize, control and analyze scenarios:

- enhanced scenario management
  Whereas DUET offers some basic management of what-if scenarios, existing GUI's and scripting tools of mature domain-specific modeling software obviously offer a richer scenario management environment; best practices could be inventoried and developed or incorporated in the DUET platform.

- optimization and control tools
  A typical use case of a digital twin is the exploration how a user might change the outcome of some of his KPI's of interest by changing the decision variables through which he controls part of the world modelled in the Digital Twin. Exploration of options can be supported by offering, for example:
  - sensitivity information of KPI for changes in the decision variables,
  - optimization (goal-seeking) of KPIs: which combination of decision variables maximizes given objectives?
  - pareto front exploration: while some KPIs can be simultaneously improved (i.e. when they are aligned), others are conflicting and form a so-called pareto-front (i.e. the collection of point for which improvement of one KPI can only be achieved by negatively affecting at least one of the other KPIs of interest). For decision makers, it is very helpful when a modeling tool assists in (semi-)automatically finding the pareto front, herewith revealing the trade-offs in the user's decision making.

6 Conclusion

This deliverable is an update and complement of "D3.3: Smart City domains, models and interaction frameworks v1". That report described the models that the technical partners (namely TNO, P4ALL and KUL) provided as input to integrate into the DUET digital twin: models for private Traffic, Air Quality and Noise. Some models needed modifications or development of additional modules for integration in DUET, notably the static and dynamic traffic models by KUL and the demand generation tool; these developments have been reported in this document.

The report started with a broader review in Chapter 3 of Smart City domains as candidates for integrating models in an urban Digital Twin. It elaborated on traffic-centered models and traffic-related impact models and discussed how – even in this single Smart City domain – a variety of submodules and interactions need to be captured. The current traffic models in DUET, for instance, focus on the operational level where the impact of route choice on loads and externalities (air quality, noise) can be investigated. Other decisions like modal choice, departure choice and activity location choice, as well as other activity and spatial decisions at the demand side of person mobility, require complementary model sets. The report creates awareness of the trade-offs that need to be made between broader scope and higher resolution. Moreover, even at high resolution, any traffic model will inevitably be more valid in predicting aggregate flows (e.g. at major roads like arterials and motorways) as compared to local traffic. A final general discussion on Smart City domains in digital twins was that of synchronization frequency with the physical world: the models require different data and calibration techniques, depending on its use is intended for second-to-second real-time tracking for short-term prediction, day-to-day tracking for next-day predictions, or tracking of slow-moving changes for strategic impact of changes to infrastructure or activities.

The focus of Chapter 4 then shifted to the digital twin domains and models specifically within DUET. It recapitulated the available traffic and traffic impact models:

- Static Traffic Assignment modules of KUL
- LTM Dynamic Traffic Assignment model of KUL
- Traffic Modeller static traffic assignment of P4All
- NoiseModelling of P4All
- Urban Strategy air quality and noise model of TNO
- CityFlows local traffic model of Imec

Scope and resolution levels of these models were then compared to the user needs (epics and user stories) resulting from the stakeholder consultation that was reported in deliverables D2.2 & 2.3 of DUET. We concluded that the match is still partial: while impact models need little modification and indeed users see added value in the integrated consultation of (multiple) traffic models and traffic impact models, for some user stories, the scope of traffic models should evolve towards a higher level of detail (more local scope), and towards inclusion of alternative modes to car travel (ideally including parking, modal shift and multimodal trip making).

For integration into the DUET platform, some models required modification. The report described the integration of KUL's separate Static and Dynamic Traffic Assignment modules into an uniform package Dyntapy; for all models a model client and technical interaction framework was created. To facilitate the set up and calibration of new cases (e.g. integrate new cities into DUET), a network and demand generation module has been developed that auto-configures an initial traffic model for the given case, which then needs further calibration and fine-tuning.

With the domain models of Chapter 4 integrated in DUET, an outlook was made in Chapter 5 of desired developments and user needs beyond DUET. This entails development directions for the models already included in DUET towards more fine-grained validity, multi-period assessment, and a wider variety of outputs. But also inclusion of complementary aspects within the traffic and mobility domain (e.g. parking, transit, pedestrians, cyclists, mobility as a service) and in connected Smart City domains like population modeling, city logistics, housing/land-use, energy system. Such endeavor would require development of a broader urban digital twin ontology formally describing all relevant entities and their properties that models and data should quantify in existing and what-if scenarios. Finally, some advanced digital twin functionality has been proposed for supporting the users in setting up cases and scenarios, and optimizing their decision variables for achieving their objectives.

Annex A Dyntapy traffic assignment

A.1. Introducing Dyntapy

To make our modelling tools more accessible to the public and to make integration with projects such as DUET easier we have transitioned away from MATLAB and developed a fully open-source traffic modelling toolkit called Dyntapy (short for Dynamic Traffic Assignment in Python). The project is hosted on KU Leuven's GitLab server, see here and is available in the Python Package Index.

We give a brief overview of the status and an outlook on what is yet to be developed.

The toolkit is meant to facilitate open research in traffic assignments. It provides the following functionalities: (1) Extraction of road networks from OSM with rough capacity estimates (2) Static User Equilibrium Assignment Algorithms such as Frank-Wolfe, Method of Successive Averages (MSA) and Dial's Algorithm B; (3) Dynamic User Equilibrium Traffic Assignment using the iterative Link Transmission model; (4) Visualization of networks and assignment states for both dynamic and static assignments.

We show a selection of these functionalities in the figures below. The reader is invited to visit the repository and go through the tutorials on Binder themselves.

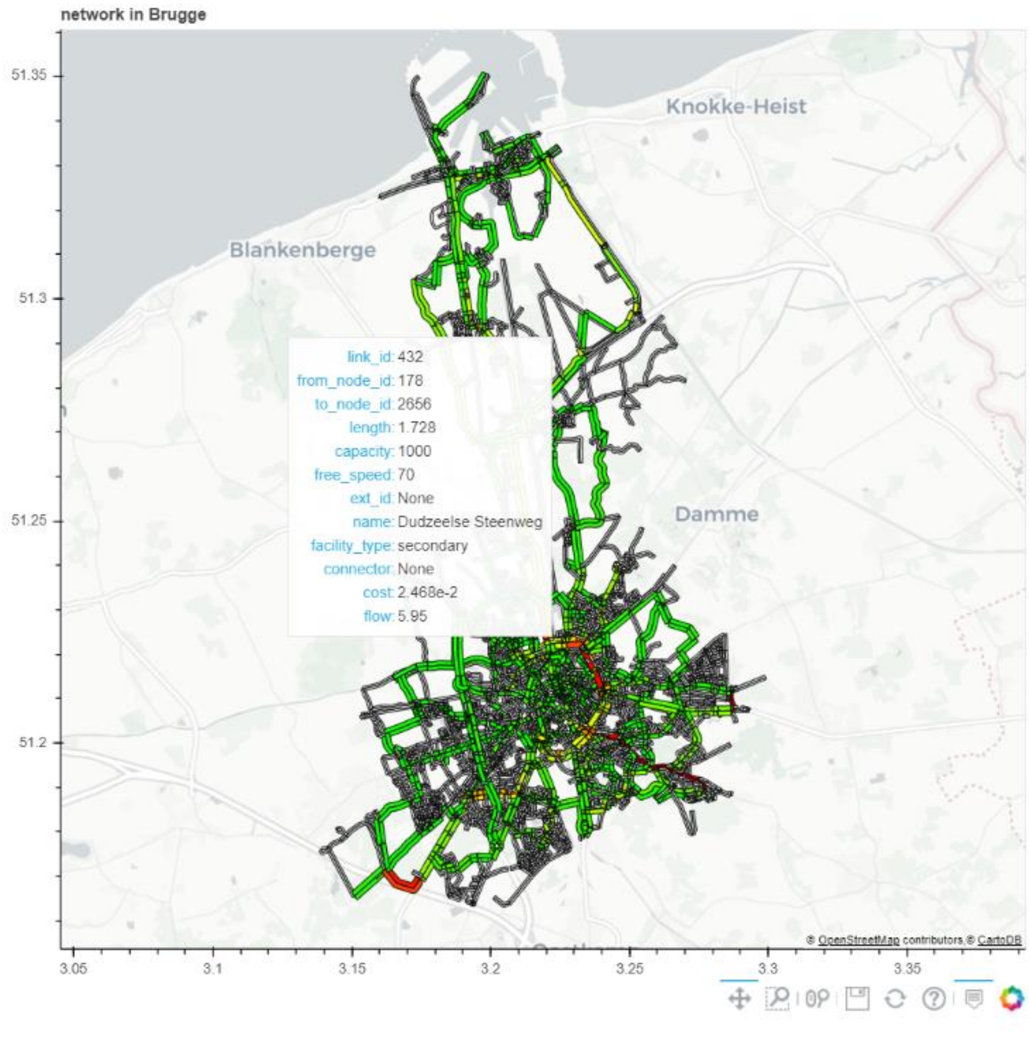


Figure A.1: Static Traffic Assignment in Bruges, 8-9 Morning Peak

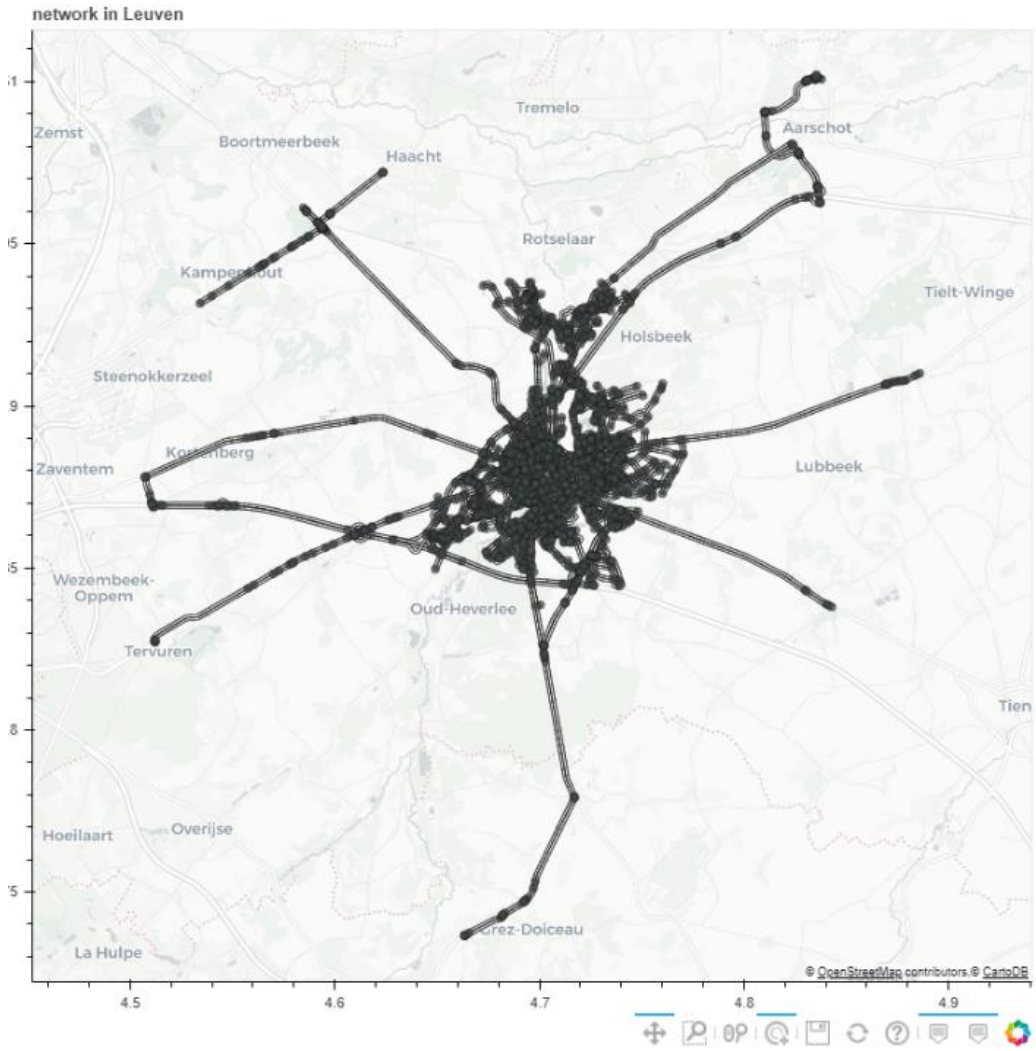


Figure A.2: Larger network extent extracted for the area of Leuven with coarser network definition in the city's surroundings.

While extracting the network for a study area of interest, the user can define buffers around the city in which a subset of roads (highways, primary roads, secondary roads ..) should be extracted and merged with the polygon of the city in which the full network detail is available. This is often used in transportation models to adequately model travellers that are passing through your study area without explicitly modelling all the lower-level links for the whole extent of the modelled territory. Including all this network detail would have an adverse effect on model performance.

We are currently working on extending this by:

- incorporating Selected Link Analysis, which exposes the travelers' origins and destinations for a given street in the network in a visual representation
- providing detailed assignment results such as impedance matrices (skims) on a zonal level

After these refinements we aim for a publication for this package in 2022.

A.2. Platform Integration

Both Static and Dynamic Traffic Assignment Models have been integrated into the DUET platform via docker containers. These container images have a local installation of Dyntapy and run a model agent that takes care of communicating with the platform. The model agent itself handles:

- processing network changes: it listens to and processes messages on a predefined topic for network changes as described in D4.3.
- translates them to an internal representation that can be understood by Dyntapy and triggers a new computation
- translates and publishes a new result in the format as put forward in D4.3

The data itself is hosted on a blob service from Azure. Computations are differentiated by passing on a scenario-id, as explained more extensively in D3.5.

Upon model creation the model agent publishes a new network and reference calculation to the platform. Demand Data is extracted from a larger model for the Flemish region if the city in question is part of Flanders (See annex B).

The model registration cannot be done by the modeler since the model catalogue is not finished at the time of writing. To connect (a set of) new models to the platform, topics need to be created manually by a system administrator. The system administrator also needs to supply a set of client ids for the models for them to receive the right subset of messages that are flowing through the platform. By doing so he sets the order of computations of models (dependency).

A.3. Performance Issues in DTA

The static models that are integrated in the platform compute in a matter of minutes and still fit well within the interactive environment that DUET wants to present to the user. The provided dynamic assignments cannot be computed in such short time periods. It is common that these models need to run overnight even for mid-sized cities such as Antwerp.

Dyntapy is using OpenMP to parallelize route choice computations, but this does not sufficiently alleviate the computational issues of Dynamic Traffic Assignment. More research is needed to handle larger DTA problems and reduce the computation time needed for larger instances. The Matlab implementation of the iterative Link Transmission Model[18] that is being converted into Dyntapy can take advantage of warm starting: they exploit a previously computed assignment state and re-equilibrate based on the changes that occurred in either the network or the travel demand. While this capability has been shown to significantly increase computational efficiency in Matlab[19], it has not yet been integrated into DUET's Dyntapy model agent due to some technical challenges. It would be worthwhile in the future to expose this since it enables fast what-if analysis for changes in the network.

A.4. Modelling of intrazonal flows

As shown in Annex B, Static and Dynamic Traffic models use zones as aggregation units of differentiating between travelers. In the loading of the network, travelers use paths connecting two artificial points (centroids), the service level of people travelling from an origin to a destination is also evaluated as the connection between these two points. This is a simplification that works well for regional transportation models in which the trips that happen on the zonal level and the flows on those local links are not relevant to the outcome of a study (i.e. the intrazonal part of the trip that is simplified by the centroid connector is short compared to the entire trip). However, in a digital twin that is focused on a city as the main stakeholder, policy makers are often interested in the outcome of a what-if analysis on the neighborhood level. This is at odds

[18] Himpe, W., n.d. Link Transmission Model download page [WWW Document]. URL https://www.mech.kuleuven.be/en/cib/traffic/downloads

[19] Himpe, W., 2016. Integrated Algorithms For Repeated Dynamic Traffic Assignments: The Iterative Link Transmission Model With Equilibrium Assignment Procedure (Dissertation thesis). KU Leuven, Leuven, Belgium.

with the connector centroid paradigm. We simply cannot trust the flows that are generated on the links surrounding a centroid because they are highly dependent on the layout of the centroids and connectors themselves. To address these challenges, we are working towards detaching zonal route choice from the (zone to zone) equilibrium process. We have, on the short term, no ambition to model the parking behavior explicitly here but want to find a way to incorporate it in a simplified manner that does not have the shortcomings of the connector centroid paradigm. This is still a topic of active research and is something we want to gain more experience with within DUET.

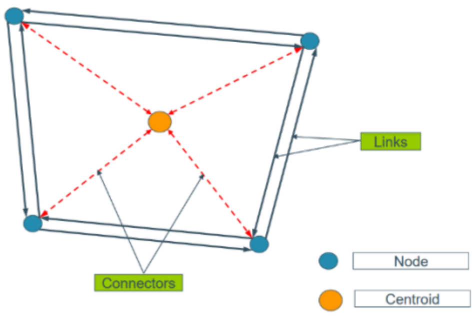


Figure A.3: Centroids and connectors visualized

Annex B: Poidpy demand generation tool

B.1. Introduction

Typical transport models have two main components: 1) A travel demand model which produces, as the name suggests, the travel demand from each modelled origin to each modelled destination and for each modelled mode of transport. 2) A traffic assignment model which assigns or loads the given travel demand onto the physical network (infrastructure) considering the route choices made by the users (usually influenced by the total travel times that different routes offer). This research concerns the 1st component i.e., the modelling of travel demand.

There are two major approaches, common both in literature and practice, for modelling the travel demand: 1) Trip-based demand modelling (Juan de Dios Ortúzar 2011) and 2) Activity-based demand modelling (Joe Castiglione 2014). The former is considered, formally, to comprise the first 3 steps of the traditional 4 step transport model but in terms of usage, both these models actually correspond to these three steps. They aim to present the travel demand in the form of an origin-destination (OD) matrix consisting of all trips between the Traffic Analysis Zones (TAZs). This OD matrix can then be assigned on the physical network using an appropriate traffic assignment model.

In **Trip-based demand modelling**, such an OD matrix is obtained following 3 sequential and mutually independent steps. In the first step, called the trip generation, production and attraction representing, respectively, the number of trips originating and ending in each TAZ are estimated. In the second step, namely the trip distribution step, the produced trips are distributed over the different destinations and attracted trips are distributed over the different origins. Finally, a mode choice model is used to have an OD matrix per mode. Trip-based demand models can be initiated (production step) either by using 1.1) Zonal characteristics as observable variables e.g., the number of residential buildings, no. of shops, population density, average household income in the zone etc. In this case, a parameter corresponding to each of these variables is estimated and holds for all zones or by using 1.2) Household characteristics as observable variables e.g., the household income, no. of cars per household, no. of workers per household etc. In this case, a parameter corresponding to each of these variables is estimated and holds only for a particular zone. Once these parameters are known, they can be used to estimate the no. of trips produced by each household which can then be summed together to get zonal production (NB: attraction step uses zonal characteristics in both cases). The trip-based demand models based on household characteristics are usually preferred over those based on zonal characteristics; however, they require much more detailed/disaggregate data for estimation/calibration as more parameters need to be estimated.

Activity-based demand models are fundamentally different from the trip-based demand models. Unlike the latter, they don't use individual person trip as the fundamental unit of analysis but instead view travel as a derived demand; derived from the need to pursue activities distributed in space (K. W. Axhausen 1992). Another fundamental difference is that trip-based demand models begin by producing aggregate estimates of demand and then at each subsequent step some disaggregation is carried out e.g., aggregate productions-attractions to OD matrix to OD matrix per mode whereas activity-based demand models work in a contrasting way. They are typically implemented using a disaggregate microsimulation framework, in which the choices are predicted at various decision-making levels such as households or individuals (Joe Castiglione 2014). As a result, disaggregate estimates of demand are predicted in the beginning, and then these estimates are aggregated sequentially by geography, time of day, mode etc. for input in the traffic assignment model. This allows these models, unlike the trip-based demand models, to recognize the relations between the locations, travel modes, and timing of travel made by an individual. They can be used to model the multi-stop trips e.g., from home to work to supermarket and back to home which, in the trip-based approach, will be modelled as two individual trips i.e., home to work and home to supermarket. Further, they recognise that mode of all parts of this multi-stop trip is fixed at once even though, when these trips are modelled individually, it might be more favourable to choose different modes. These models also account for the details of individual travellers and their coordination with other household members e.g. usage of family cars. Although these models can be used to carry out much more detailed analyses than the trip-based demand models, they are also more difficult to set up. Their data requirements are much more arduous even than the trip-based demand models using household characteristics. The household surveys for recording activities need to have a much larger sample size due to the consideration of a wide-variety of socio-demographic variables and types of choice alternatives. They also need to be strictly complete and consistent in the sense that they account for joint travel decisions and coordinated activity scheduling across household members (Joe Castiglione 2014). Further, a much more detailed demographic information that records each individual and can be used to synthesize a synthetic population is required. In terms of land-use data (to be used for location choices for carrying out activities), for a given zoning, similar data can be used for both trip-based demand models and activity-based demand models.

In conclusion, there is consensus that in simplicity (and ease) of setup, implementation and result-analysis, the trip-based demand models using zonal characteristics are ranked higher than the trip-based demand models using household characteristics which are ranked higher than the activity-based demand modelling. On the other hand, in terms of accuracy and ability to assess detailed impacts of detailed policies, the ranking order is reverse.

On another note, volunteer-based geographic information (VGI) systems like OpenStreetMap (OSM): “a collaborative project to create a free editable geographic database of the world”, have become increasingly popular and trust-worthy in recent times. OSM gives open access to the point-of-interest (POI) information revealing highly disaggregate geospatial data about land-use in a given region. This land-use data forms a crucial part of the input data required to build almost every type of travel demand model including the three mentioned earlier. Usually, such data is extracted from census and spatial data made available by the government. Further, this is generally available only for a particular type of zoning which makes the travel demand models somewhat inflexible. The availability of this data from OSM and that too at a highly disaggregate scale and for any region of choice has the potential to obviate this inflexibility and reduce the dependency on government having jurisdiction over the region. When combined with the adequate additional data e.g., socio-demographic data, it can even be used in the process of building activity-based demand models for the concerned region.

The aim of this research is to provide proof of this concept by extracting land-use data for a certain Flemish region from OSM, combining it with some other types of available data and estimating/building a travel demand model for the corresponding region. Since activity-based demand models and trip-based demand models using household characteristics have stricter and more arduous data requirements, the type of model chosen for this initial exercise is trip-based demand model using zonal characteristics. This choice is neither based on nor an indication of the superiority of this particular type of model over others for the region and policy to be considered but is, rather, totally motivated from the objective of showcasing that OSM data can be used to build travel demand models and the chosen type of model allows to do this with minimum amount of additional data requirement. For the initial exercise, we generated from OSM data an OD matrix for different study areas of the Flanders pilot region and compared them to a reference OD matrix available from Mobiliteit en Openbare Werken (MOW). Once the parameters of the transformation of OSM data into OD-flows are estimated, it is also intended to experiment with new TAZ definitions (modification of sizes or boundaries) using the estimated parameters. Since these parameters correspond to variables like no. of single residential buildings in the zone, they can be directly combined with the new value of such variables in the new TAZs. This will allow analyzing the impact of varying TAZ definitions which are presently constrained to those provided by the government. Additionally, certain variables/attributes e.g., availability of parking spaces/bus stops within a zone and its neighbouring zones, presence of special buildings like stadiums, arenas etc. can be accounted for. Such attributes are not usually used in traditional production-attraction models due to lack of data. Once estimated, this model should allow for analysis involving removal, addition or relocation of individual POIs on travel demand. Further, an analysis of the transferability of estimated parameters to different but comparable regions is also foreseen. If successful, it has the potential to obviate even the need of an apriori available OD matrix or household travel surveys for building a crude travel demand model for such a region. Two versions of the goal of this research are stated as follows:

- *Preliminary goal: Estimate travel demand model for any region using publicly available Point-of-interest (POI) data and an apriori available OD matrix.*
- *Ultimate goal (Optimistic): Estimate travel demand for any region (real or derived from real) using publicly available Point-of-interest (POI) data, independent of specified traffic analysis zones and without using travel surveys (or OD matrix).*

In the next sections, the methodology of extracting POIs from OSM is discussed followed by a discussion of the traditional steps of the trip-based demand modelling using zonal characteristics.

B.2. Methodology

This section describes the methodology applied. The methodology can be divided into five parts: study area definition, POI data extraction and pre-processing, the creation of the residential and activity layers, trip generation, and trip distribution (see Figure 1).

Figure 1: Methodology

1. Study area definition

The first step in the demand generation process is to delineate the study area for which an OD matrix will be generated. Moreover, this study area should be divided into traffic analysis zones. It is recommendable to ensure the zoning is homogeneous in terms of total production/attraction; this means refinement of the busy zones and aggregation of the quieter ones, such that the order of magnitude of total production/attraction is comparable over zones. Otherwise, corrections to a single zone with higher demand might come at the cost of larger errors in a multitude of lower-demand zones, while still seemingly improving the overall fit while in fact, the structure of demand is badly captured.

Besides the actual study area, including internal zones, a traffic model typically also considers an area of influence, which includes any nearby cities or settlements in the surroundings of the study area. This is because a considerable number of trips may be made into or out of the study area from or to these surrounding cities, defined as external zones. For the time being, in this research, no external demand has been taken into account yet.

2. POI data extraction and preprocessing

This section describes the design choices made concerning the data downloaded from OSM as well as the pre-processing methods applied to attain a consistent data set of POIs. An overview is given in Figure 2. The method developed utilizes the OSMNx package for interacting with the OSM API.

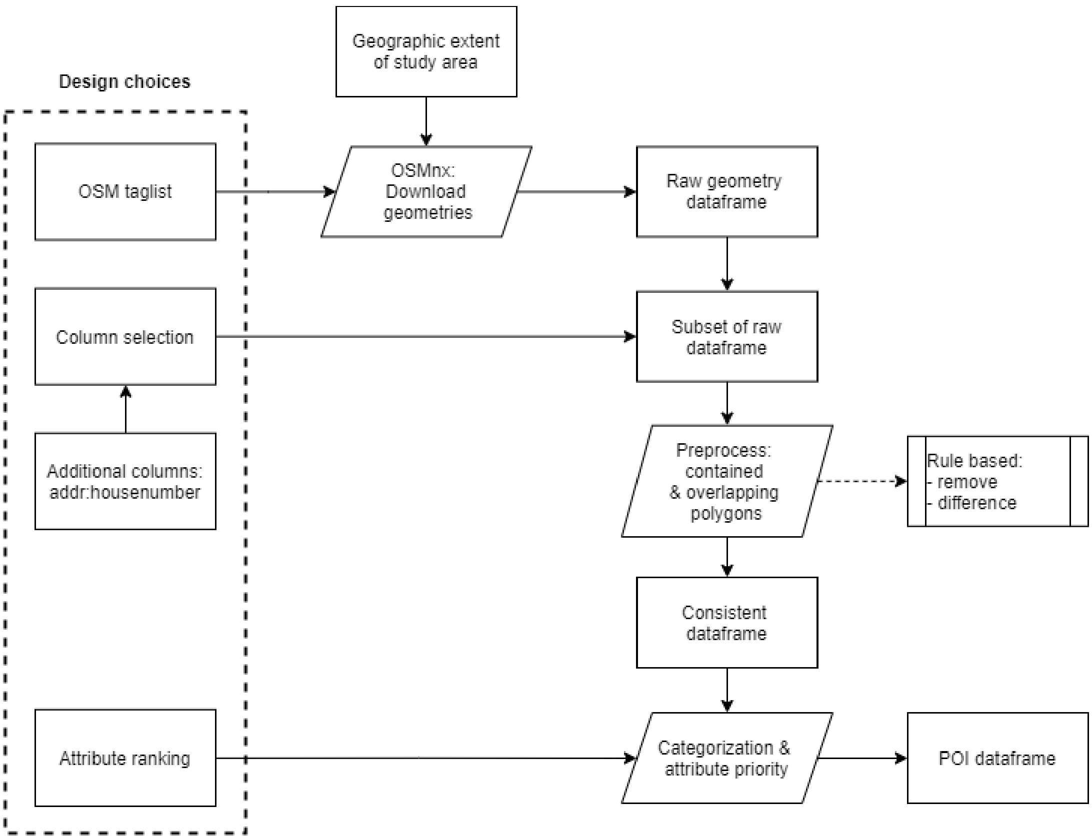


Figure 2: POI data extraction and pre-processing

OSM is a collection of physical objects present in the world. It uses a tagging system to store relevant information as attributes attached to the objects[20]. It is essentially a key-value database in which the tags and associated values attached can differ from object to object. There is a large difference in attribute usage as well as heterogeneity in the values. Some values are almost never used, non-English or typos but nevertheless the value set remains highly heterogeneous[21,22]. This is the result of OSM being a VGI system. The quality of the datasets that are generated in this way vary widely between regions and depend on the diligence of the local contributors[23].

The first design decision made concerns the downloaded data from OSM. A selection of relevant attributes is passed on as parameter in the OSM download module together with extensive lists of attribute values to limit the number of irrelevant features polluting the data set. The selection of attributes and values follows from previous knowledge[24] and additional information from OSM Wiki[2] and taginfo[3] (see Table 12 in Appendix B1). The filtering is only done for the *amenity, building, landuse* and *leisure* attributes since the others inherently possess more homogeneous information through their attribute name. Nevertheless, it is important to note that these tag lists are dynamic and including or excluding values is certainly encouraged. Future approaches can try some big data and AI techniques to automate this process further.

The second design choice concerns the consideration of additional attributes that help to extend the information about a specific feature. In this project, the *addr:housenumber* attribute is considered to gather

[20] https://wiki.openstreetmap.org/wiki/Map_features
[21] Wiki page with information about all sorts of tags and values: https://wiki.openstreetmap.org/wiki/Main_Page
[22] Database with metadata on all tags: https://taginfo.openstreetmap.org
[23] Jean-François Girres and Guillaume Touya, "Quality Assessment of the French OpenStreetMap Dataset," Transactions in GIS 14, no. 4 (2010): 435–459.
[24] Griffiths, H., 2020. A New Method for Determining Traffic Demand Using Open Data (Masters Thesis). KU Leuven Faculteit Ingenieurswetenschappen, Leuven.

information on the house number of buildings. The resulting geodataframe, geographic data set, contains all the extracted objects, also called geometries, from OSM, together with the chosen attributes.

Ideally the spatial data extracted from OSM is complete, accurate and consistent, unfortunately this is not the case. Spatial data in OSM exists in three types namely, points, linestrings and polygons. For POI information, only points and polygons are of interest, assuming a line feature is not a POI. Moreover, there are also some faulty or inaccurate mappings making the layer spatially inconsistent. This needs processing to flatten all POI information to only one layer where the relevant information is combined, and the spatial layer is consistent. In this way, ambiguity in later analyses is avoided.

Two types of inconsistencies are handled: contained polygons and overlapping polygons. These inconsistencies only apply to polygon features, and they are only resolved for objects with a value for the *building* attribute and objects with only a value for the *landuse* attribute. For these attributes it is illogical to have more than one structure or function at the same location. For example, an area with a specific land use should not contain a zone with another land use, since this implies a new land use consisting of the combination of the others which is an unwanted situation. The same applies to buildings. Having another function inside a building is possible but the structure as such consists only of one building or two individual non-overlapping buildings. Although the processing steps are not complex, the pragmatic choices to resolve conflicts impact the final consistent layer.

For contained polygons two possibilities are put forward: *removing the contained polygon* leaves out the polygon within the other and *the difference method* cuts out the contained polygon from the other one. For the building polygons, the first approach is chosen and for the landuse polygons, the second method is preferred.

For overlapping polygons, depending on the overlap ratio, *the overlapping area is removed* from the smallest polygon, or *the smallest polygon is fully dropped*. The former assumes the polygons to be two independent features if the overlap ratio is smaller than a specified threshold and the latter assumes the smallest polygon to be part of/within the larger polygon if the overlap ratio is larger than the specified threshold. The overlap ratio is specified as the ratio of the overlapping area with the area of the smallest polygon. The attribute information of removed objects is not transferred, since these inconsistencies are due to bad mapping practices. For both the building and landuse polygons, the threshold is set to 0.5.

The resulting data set is still multi-layered but when geometrical operations are applied no inconsistencies are encountered.

The last pre-processing step concerns the classification of the geometries. All features are classified in multiple categories for each attribute according to the corresponding attribute value. For every attribute, this classification is based on the key specific OSM wiki pages[25]. These store lists with widely accepted values classified into distinct categories. For example, for the *building* attribute a categorization into *accommodation, commercial, religious, civic/amenity, agricultural/plant production, sports, storage, cars, power/technical buildings,* and *other buildings* exist. Such a classification also exists for the *landuse, amenity* and *shop* attributes. For the *leisure, sport, tourism* and *office* attributes no categorization is available, nor considered.

The third and last design decision concerns the ranking of attributes according to importance. The extracted geometries may have non-null values for multiple attributes and hence, be classified in various categories. Therefore, this approach specifies a priority ranking to reduce the multi-dimensionality to only one dimension, making further processing easier. The priority is as follows from low to high priority:

landuse < building < amenity < tourism < sport < leisure < office < shop

[25] https://wiki.openstreetmap.org/wiki/Key:landuse, https://wiki.openstreetmap.org/wiki/Key:building, https://wiki.openstreetmap.org/wiki/Key:amenity, https://wiki.openstreetmap.org/wiki/Key:shop, https://wiki.openstreetmap.org/wiki/Key:office, https://wiki.openstreetmap.org/wiki/Key:leisure

This priority ranking is a quite strict design choice, but a check reveals that only few features have multiple labels. Mostly the combination of a *building = yes* with another attribute value is present or a value for *leisure* and *sport*. An alternative could be to make a hierarchical tree structure to decide on the function of a feature but currently this priority ranking does the job.

3. Creation of unidimensional POI-layers

Up until this point, the methodology creates a consistent data set of all the features with values for the chosen attributes. The next step uses this pre-processed data to create separate unidimensional layers for the residential and activity type. These created layers are unidimensional spatial layers, meaning they can easily be used for geometrical processing and analysis without worrying about the information for multiple attributes. The two types of layers can be summarized by two questions: Where do people reside? Where do people do things? These insights in origins and destinations serve as the starting point to estimate travel between regions.

Residential layer

Selecting all those geometries with the right attribute values should suffice to create a layer containing all residences classified by type for a region. However, the labelling of objects is sometimes incomplete or incoherent making the need for some simple filtering methods necessary to correctly infer the type of housing. Figure 3 depicts the process to attain a unidimensional layer with residences of different types depending on the available information. Knowing most residential buildings are included in OSM as a polygon instead of a point, focus is given to polygons with *attribute_priority = building*. Next, based on the categorization *category_building = accommodation*, a first selection of residential buildings is made. However, a lot of features miss detailed information to immediately label them residential, such as features with the tag *building=yes*, and hence, *category_building = other*. Therefore, some basic decision rules are used which are shortly explained below:

- **intersection with other features**: when a building feature is in any way intersecting with more than one feature it will not be a residence, probably (e.g. shopping centre).
- ***Landuse = residential*** : features inside a residential land use area are likely to be residences.
- **house number**: features with a value for the *addr:housenumber* attribute are more likely to be residences than features with no house number.
- **area threshold**: those features without a house number but within a residential land use area should have a polygon area larger than a specified threshold (e.g. garden sheds will not be taken into account).

Applying this framework, six types of houses are distinguished, three of them follow from available attribute information (*large residential*, *student residential* and *single residential*). The other types (*yes house number residential land use*, *yes house number no residential land use*, *yes no house number residential land use*) classify the undefined building features in accordance with the applied rules. Those having only the minimal requirements possess the lowest certainty. The advantage of distinguishing between these types is the extra flexibility to take this certainty into account in further stages.

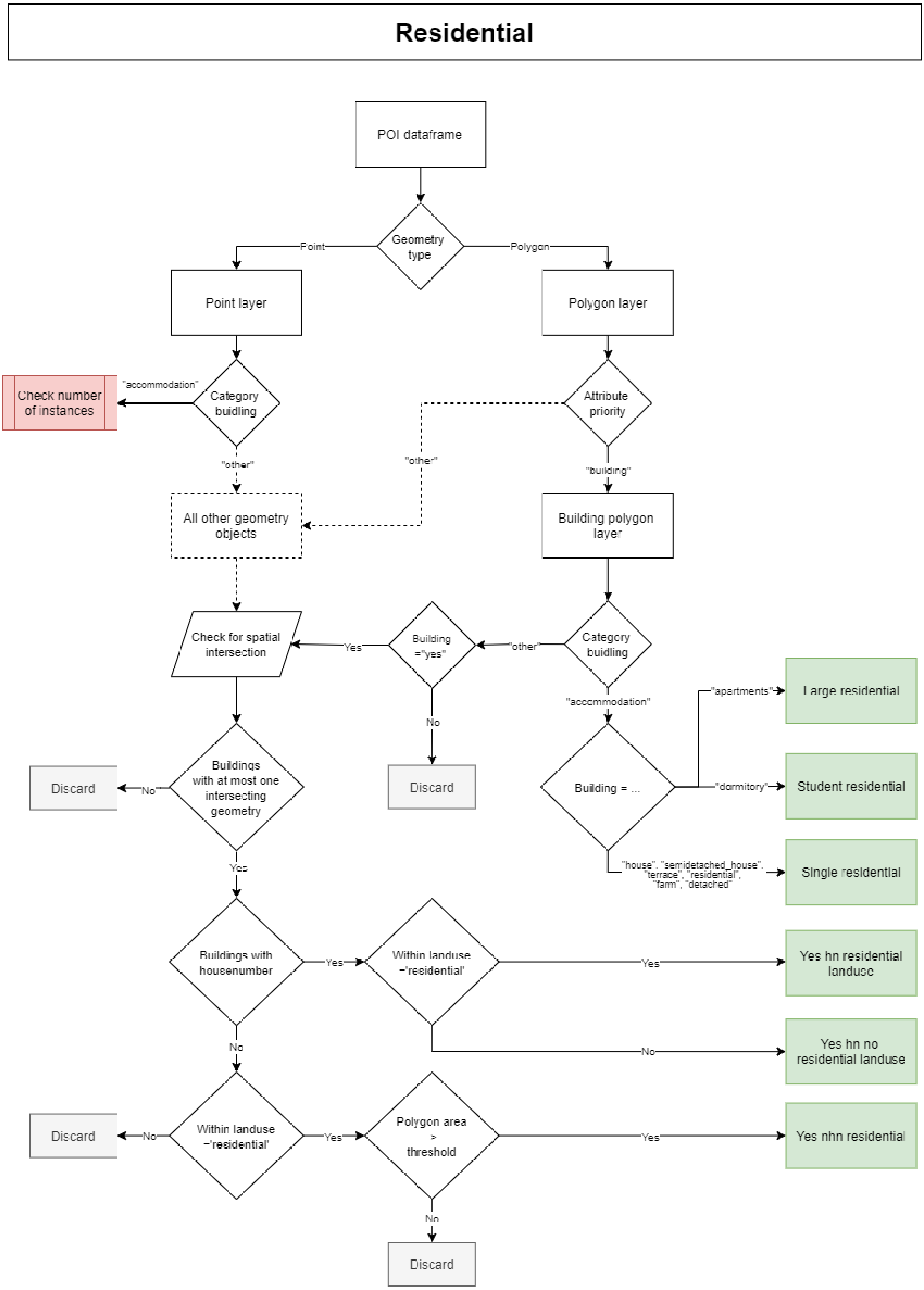


Figure 3: Residential layer creation

Activity layer

The approach to create the activity layer also starts from the pre-processed POI dataset. However, it disregards the objects already included in the residential layer as well as polygon objects with only a value for the *landuse* attribute, i.e., the *landuse* attribute has highest priority. The approach differs from the classification process of residential buildings as it considers both point and polygon objects and infers information of surrounding features to decide on whether to include a feature in the resulting activity layer.

The approach for inferring information of surrounding features is visualized in Figure 4. It is done for three types of features: points, buildings, and non-building polygons. The difference between a point and polygon is clear via the geometry type. The difference between building and non-building polygons (e.g. parks, recreation ground, pitch, playground, …) follows from having a value for the *building* attribute or not. For each feature, information on a primary and secondary attribute-value pair are stored. The primary attribute and value are derived from the feature itself. It is the highest ranked attribute for which a value is available. The secondary attribute and associated value follow from the attribute priority from the surrounding features. Of course, if a feature is not intersecting with another one, no secondary values are considered.

For non-intersecting objects with attribute priority *building* and only having *building = yes* as information an additional step is performed in which information on *landuse* is used to infer the activity type. Those features that are located inside a polygon with *landuse* value *commercial, industrial, retail* or *recreation_ground*, and have an area larger than a specified threshold, get the *landuse* value of the surrounding polygon assigned as primary value on which they will be classified further on.

For the classification, the NACE[26] classification system is used. This classification based on an external source was deemed necessary given the high variety of attribute values and to standardize the classification process such that later-on it will be easier to attribute external data sources to the spatial features. The first classification level is shown in

Table 1. This contains the letter codes for 21 different activity class. Classes A, B, D, E, F and U are disregarded. Going over the attribute-value pairs, every pair is mapped manually to an activity class. The result is given in Appendix B2 (Table 13).

Using both the values from the priority/primary and secondary attribute, the features are manually classified according to the NACE classification system, resulting in a primary and secondary activity class. Features not assigned to any class or those having the same primary and secondary class are left out of the activity layer. Having the same primary and secondary class means the feature is inside a polygon with similar purpose. For example, this could be the case for shops which are represented in OSM as a polygon as well as a point. As the surrounding feature is still in the dataset, these contained feature are dropped to avoid a POI is included multiple times in the activity layer. This filtering depends heavily on the mapping choices and completeness of the considered attribute-value pairs.

This results in a POI layer with a reduced dimension, since the multi-layer is flattened to one layer where every POI has one function and no duplicate features are present, e.g. a point object and building object with same function are not both present. Additionally, this step also removes an overestimation of POIs resulting from groups of points or buildings within a polygon of one type, e.g. all research buildings of a university within the polygon encompassing the whole campus.

[26] The standardized classification for the whole EU: https://ec.europa.eu/competition/mergers/cases/index/nace_all.html

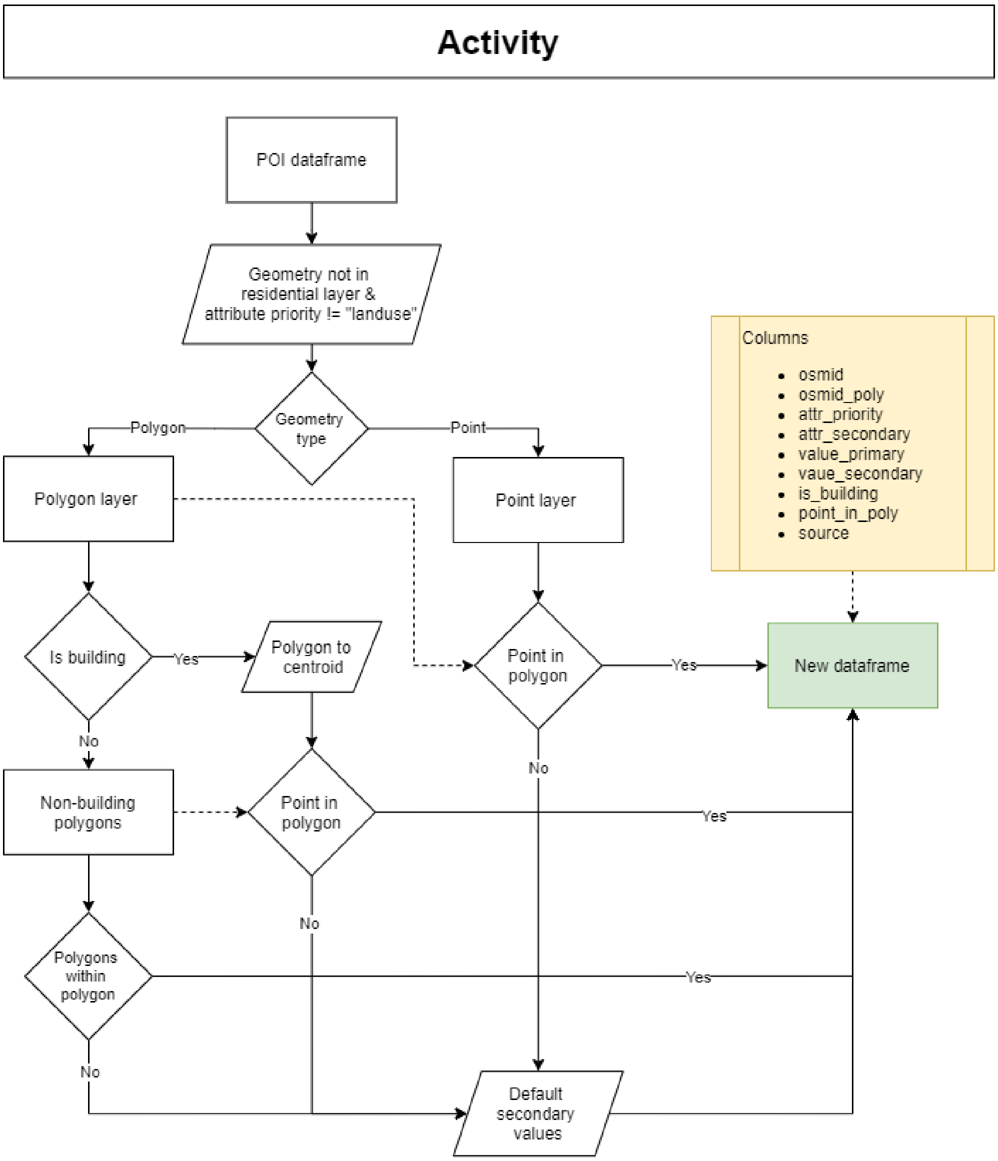


Figure 4: Dimension reduction activity layer

Table 1: NACE classification

NACE	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage; waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organisations and bodies

4. Trip Generation

Both the created residential and activity layer give insights in possible origins and destination locations of trips. The number of POIs in the different categories can serve as the starting point to estimate travel between regions. Different demand modelling techniques such as factor analysis, linear regression or discrete choice models exist[27]. In this paper, linear regression is used as the technique for trip generation.

A multiple linear regression finds the trip rate coefficients for the different POI classes. Equation (1) shows the formulation of the regression model.

$$T_i = \beta_0 + \sum_n \beta_n X_{ni} \qquad n = 1, .., n;\ i \in zones \qquad (1)$$

With T_i the number of trips, $\beta_0$the intercept and β_n the coefficient of variable n and X_{ni} the number of POIs from class n in zone i.

Data from other transport models are used for training the regression model. Typically, production- and attraction models are handled separately and further differentiated by the trip's purpose and time of day. Two models will be calibrated for the estimation of production and attraction, separately. They will focus on the morning peak car traffic including all trip purposes. The calibration of the models is further explained in the section on

Model calibration.

[27] Ortúzar, J.D. and Willumsen, L.G. (2011) Modelling Transport. 4th Edition, Chichester, West Sussex, England: Wiley

5. Trip distribution

The last step required to obtain an OD matrix is the distribution step. From the trip generation step, the number of trips produced and attracted by each zone is known. However, there is still no idea on where trips departing in a certain zone go to and where trips arriving in a certain zone come from. The goal of a distribution model is to match trip makers' origins and destinations into actual trips.

The gravity model is used for trip distribution. It uses travel impedances/generalised travel costs between zones (travel time, travel costs, …) as measure to distribute the trips over the OD pairs. These impedances are initially estimated as the shortest path free flow travel time or distance between the centroids of each OD pair. Intuitively and from empirical research, the number of trips between a certain OD pair is negatively correlated with the travel impedance between these zones. In other words, the number of trips towards a destination will decrease if distance towards this destination increases. $F(c_{ij})$ deterrence function ￼. Different formulations for this deterrence function can be used. The negative power function, the negative exponential function, or the combined power- and exponential function are examples of available formulations in the tool. The most appropriate function often depends on the type of trips that are considered. Next, starting from the OD matrix structure filled with these deterrence values, the Furness iteration process is used to generate the OD demand matrix complying with the estimated zonal production and attraction values. In this process, the matrix is iteratively matched with the expected productions and attractions by respectively multiplying each row by a row specific growth factor g_i and each column by a column specific growth factor g_j. This iterative process is repeated until the row and column factors converge to a value of 1.0. In the end, the result can be written as follows:

$$T_{ij} = a_i \cdot b_j \cdot F(c_{ij})$$

With $a_i = g_{i,1} \cdot g_{i,2} \cdot g_{i,3} \cdot \ldots$ *and* $b_j = g_{j,1} \cdot g_{j,2} \cdot g_{j,3} \cdot \ldots$

With T_{ij} *the number of trips between origin* i *and destination* j.

B.3. Model calibration

The trip generation and trip distribution model require some parameters to be calibrated before the tool can be used to generate demand for any city. The model was calibrated for the case study of Antwerp as part of the Flemish DUET pilot. For this purpose, available demand data from the Flemish department of Mobility and Public Works (MOW) is used. It includes an OD matrix for the whole of Flanders, including external zones that represent Wallonia and the neighbouring countries.

One may wonder why we try to generate demand (OD matrix) when apparently a full Flemish OD matrix exists. If one is only interested in case studies in Flanders, with a zonal aggregation level equal to the one in the MOW reference data, and one only has interest in the base year 2030 that the MOW data refers to, the existing data are indeed sufficient. However, as land use and mobility habits evolve – and may even be a variable that one would like to study the influence of for future scenario exploration – such information would soon be outdated. The demand generation tool retrieves the OD-demand from living data sources (OSM) and/or from inputs that can be manipulated for scenario analysis by the DUET users, herewith guaranteeing that it is always up to date and that future extrapolations are consistent with currently observed demand characteristics. Also, the existing MOW zoning is coarse, while some analyses withing DUET may require smaller analysis zones. The demand generation tool then serves as a consistent disaggregation method. Finally, urban digital twins may be desired for cities that have no reference demand data; while OSM data is generic and thus exists anywhere. Then, and as a first proxy, demand can be generated with the tool, using parameters of regions for which calibration with reference OD-data has been done and that are expected to exhibit similar mobility behaviour than the new region of interest. We will demonstrate the latter use of our tool below by generating a first demand matrix for the Athens region of which no traffic model was available in DUET.

Starting from the MOW dataset, only the 193 zones of Antwerp are considered. The zones covering the harbour of Antwerp as well as the airport of Deurne were removed. Additionally, two other zones, mainly covering a large highway interchange were taken out as well. In the end, from the original dataset, 39 zones were dropped. The other 154 zones were retained as study area to perform the analysis (see Figure 5).

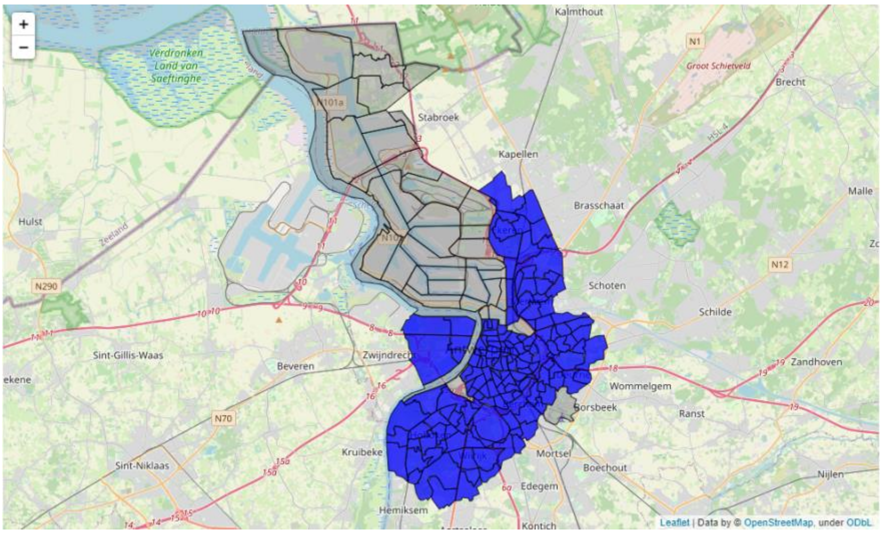


Figure 5: Antwerp study area

From the MOW matrix, only the trips made between the retained zones were extracted. No external demand was taken into account[28]. In this case study, the car travel in the morning peak is of interest. This means, only the interzonal trips made between 5am and 11am by car are considered. The total extracted trips include 85,7% of the total interzonal morning peak car travel in Antwerp. The true production and attraction per zone were calculated by, respectively, summing the values of each row (origin) and of each column (destination) in the extracted OD matrix. The result is visualised in Figure 6.

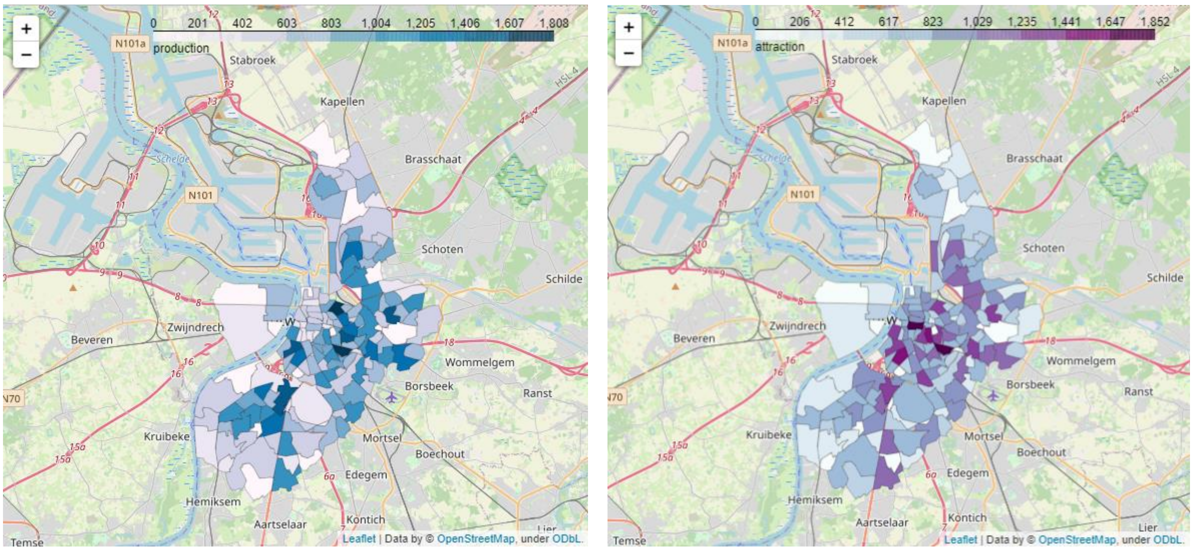


Figure 6: (a) Zonal production (b) Zonal attraction

[28] Mind that in future refinements of the demand generation tool, solutions for external traffic need to be developed

Trip generation model

The goal of the production and attraction regression models is to predict the zonal production and attraction based on the information included in the created residential and activity layers. From these layers, the number of POIs of each residential or activity class per zone has been calculated using the methods described before. For modelling the zonal production, detailed information on the residences is used. This is because the trips of interest are the ones made during the morning peak and hence, the residences can be expected as important origins of trips. Nevertheless, the morning peak trips might also already include people travelling from work or other activities to home or between activities. Therefore, an aggregate variable representing the total activity in a zone has also been considered in the production model (NB: future refinements may consider disaggregate activity variables).

Multiple linear regression was used to test if *single residential* (X_{SiR})*, large residential* (X_{LR})*, student residential* (X_{StR})*, yes building house number residential landuse* (X_{HN})*, yes building no house number residential landuse* (X_{NHN})*,* and *total activity* (X_{TA}) significantly predicted *production (P).* The model structure is:

$$P_i = \beta_{SiR}X_{SiR,i} + \beta_{LR}X_{LR,i} + \beta_{StR}X_{StR,i} + \beta_{HN}X_{HN,i} + \beta_{NHN}X_{NHN,i} + \beta_{TA}X_{TA,i} \quad (2)$$

Performing statistical outlier analyses revealed 9 zones that were biasing the regression result. Even though such zones with exceptional demand generation are real and thus should not be neglected, outlier analysis reveals that something particular happens in these zones that does not follow the general pattern. Postponing, for now, the in-depth analyses for the reasons of this deviant demand production behaviour, we first focus on extracting the general pattern. Hence, dropping these influential observations, a significant regression equation was found (*$F(4,141) = 525.6$, $p < 1.29e-83$*), with an R^2 of 0.754. The fitted regression model is:

$$P_i = 0.596 * X_{SiR,i} + 3.267 * X_{LR,i} + 0.846 * X_{HN,i} + 1.845 * X_{TA,i} \quad (2)$$

The R^2 value shows that the model describes a substantial part of the relationship between the number of different types of POIs and the number of produced trips. *Student residential* (X_{StR}) *and yes building no house number residential land-use* (X_{NHN}) were found not to be significantly predicting *production* on a 5-percent significance level (respectively, p=0.1506 and p=0.0583). The resulting model can be interpreted as follows: a single residential building, a large residential building, a building with house number in a residential area and an activity will, respectively, produce 0.596, 3.267, 0.846, and 1.845 trips. A large residential building producing more trips than a single residential building seems logical. The relatively high coefficient for the aggregate activity attribute shows that considering disaggregate activity POIs may further refine the model. Table 2 presents the estimated coefficients with their standard error, t-value, p-value, and 95%-confidence interval.

Table 2: Calibrated production model coefficients

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
count_single_residential	0.5958	0.0331	17.9996	0.0000	0.5303	0.6612
count_yes_hn_lu	0.8458	0.0310	27.3126	0.0000	0.7846	0.9070
count_large_residential	3.2670	0.8533	3.8289	0.0002	1.5802	4.9539
total_activity	1.8451	0.2825	6.5307	0.0000	1.2866	2.4036

For modelling the zonal attraction, the information on disaggregate activities is used. Following the same analogy as for zonal production, activities can be considered as the main destination of the trips during the morning peak. Additionally, an aggregate variable representing the total residential POIs in a zone is considered. This showed to improve the model. Reasons for this might be that morning peak trips also include trips made for visiting people. More importantly, intuitively it seems logic a zone with higher population will also have more activities in its neighbourhood. Following this reasoning, including the total number of residential POIs might compensate for the possible incompleteness of the activity POI data extracted from OSM.

Multiple linear regression was used to test if *the number of POIs in each NACE class (C, G, H, I, J, K, L, M, N, O, P, Q, R, S, T)* and *total residential* (X_{TR}) significantly predicted *attraction (A).* The model structure is:

$$A_i = \sum_{\substack{class \in \\ (C,G,H,I,J,K,L,M,N,O,P,Q,R,S,T)}} \beta_{class} X_{class,i} + \beta_{TR} X_{TR,i} \quad (5)$$

The outlier analysis revealed 11 zones that were highly influencing the regression result. Again, postponing in-depth explanation of these outliers and first focusing on the general pattern, we dropped, for now, these influential observations. We obtain a significant regression equation (*F(7,136) = 221.1, p < 4.91e-71*), with an R^2 of 0.640. The fitted regression model is:

$$A_i = 7.563 * X_{C,i} + 3.896 * X_{G,i} + 22.330 * X_{M,i} + 23.192 * X_{P,i} + 31.543 * X_{Q,i} + 79.990 * X_{S,i} + 0.436 * X_{TR,i} \quad (6)$$

The R^2 value shows that the selected POI types (C - industry, G - shop, M - office, P - education, Q - health, S – services, and aggregate residential) indeed explain a large part of the variation in the number of attracted trips. *Classes H, I, J, K, L, N, O, R and T* were found not to be significantly predicting *attraction* on a 5-percent significance level (respectively, p=0.4862, p=0.0564 , p=0.5858 , p=0.0729 , p=0.7506 , p=0.8029 , p=0.8866 , p=0.3150 , p=0.0938). The resulting model can be interpreted as follows: manufacturing buildings, retail stores, offices, educational places, health, other services and residences will, respectively, attract 7.563, 3.896, 22.330, 23.192, 31.543, 79.990 and 0.436 trips. Table 3 presents the estimated coefficients with their standard error, t-value, p-value, and 95%-confidence interval.

Table 3: Calibrated attraction model coefficients

	Coef.	Std.Err.	t	P>|t|	[0.025	0.975]
count_C	7.5630	1.4367	5.2643	0.0000	4.7219	10.4041
count_G	3.8956	0.8295	4.6965	0.0000	2.2553	5.5359
count_M	22.3299	7.6285	2.9272	0.0040	7.2441	37.4156
count_P	23.1916	8.2352	2.8162	0.0056	6.9060	39.4773
count_Q	31.5432	11.3525	2.7785	0.0062	9.0929	53.9935
count_S	79.9890	15.9768	5.0066	0.0000	48.3940	111.5841
total_residential	0.4364	0.0312	14.0037	0.0000	0.3748	0.4981

Trip distribution model

The goal of the trip distribution model is to distribute the produced trips (Origin) over the different destinations as well as distribute the attracted trips (Destination) over the different origins. The gravity model uses the notion of travel impedance to distribute the trips. In this case study, the travel impedance is calculated as the shortest path free flow travel time (disregarding, for now, intersection delays) between the centroids of the origin and destination zone (calculated using the Dyntapy package).

How the travel impedance relates to the number of trips towards a destination is described by the deterrence function. We applied here the combined power-exponential function:

$$F\left(c_{ij}\right) = \alpha \cdot c_{ij}^{-\beta} \cdot e^{-\gamma c_{ij}}$$

The general shape of the function is visualised in Figure 7.

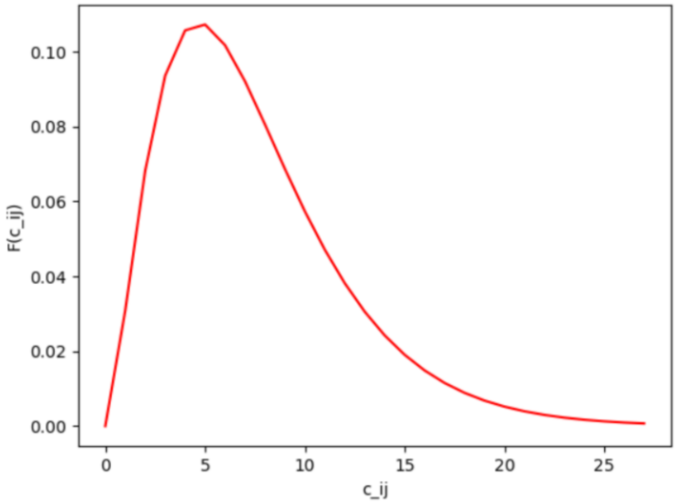


Figure 7: Combined power-exponential function

This shape is often used to describe trips by car. Initially, the function increases, before decreasing with increasing impedance. This models that for small distances, the car will not be used but walking or cycling will be preferred.

The parameters α, β, and γ should be calibrated based on observations from the study area. This is done using the extracted OD matrix from the MOW data. For each travel time range, the average number of trips made in this range is assessed. In this way, the trip cost distribution visualized in Figure 8 is derived for Antwerp.

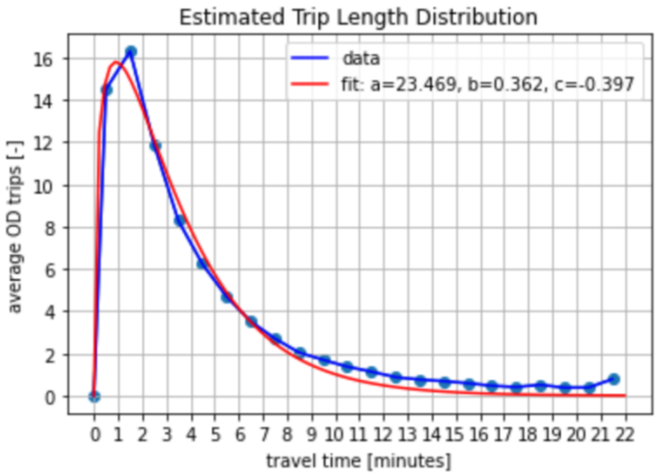


Figure 8: Calibrated deterrence function/trip cost distribution function for Antwerp

The developed tool allows the user to define any alternative deterrence function and to calibrate its parameters given an existing OD matrix. In absence of such data, one may use standard values from literature or transferred from other case studies for the function parameters. These can be manually supplied to the tool.

With this function, the shortest path free flow travel times are transformed into start values of OD trips per cell. Next, these initial values are scaled to match the desired production and attraction using the Furness iteration process to generate the OD matrix. This algorithm ensures that the sum of each row and each column become equal to, respectively, zonal production and attraction. For the algorithm to converge total production and total attraction should be equal.

B.4. Results

Antwerp

Trip generation

The performance is visualized in Figure 9. This figure compares the true production and attraction with the estimated number of trips. The R^2 values between the true and estimated values for production is 0.754 (with outliers 0.623) and for attraction is 0.640 (0.374 with outliers). These represent the magnitude of the correlation/relationship between the true and estimated values and hence to what extent the predicted values are related to the true values.

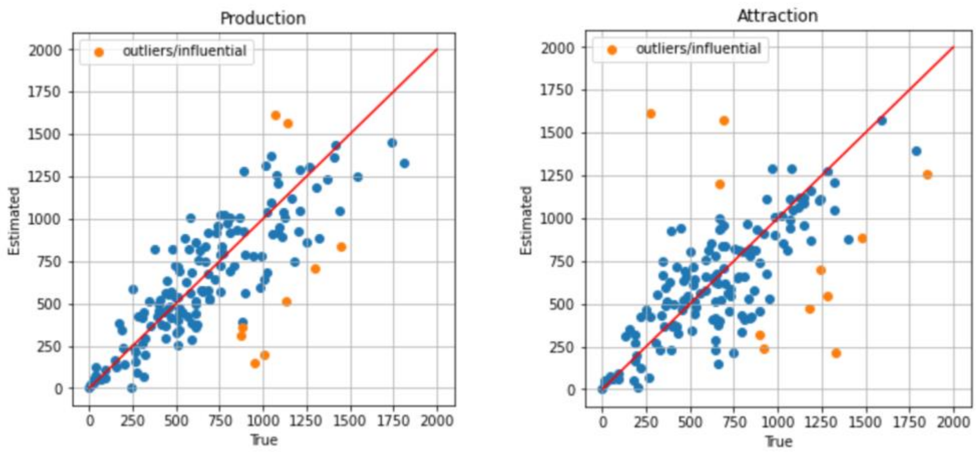


Figure 9: True and estimated (a) production and (b) attraction values

The model estimated that in total 97946.642 trips (91696.177 without outliers) are produced by all zones together whereas the actual total production is equal to 103976.652 (94177.632 without outliers). Regarding attraction, the model has a similarly satisfactory performance in terms of predicting the total attraction. The model predicts in total 97636.489 trips (88611.438 without outliers) are attracted by the zone compared to the actual total attraction of 103976.652 (92169.831 without outliers). This is an underestimation of 5.80% (2.63% without outliers) for production and 6.10 (3.86% without outliers) for attraction.

Figure 10 shows the distribution of the prediction errors for production as well as attraction. Of course, the predicted production and attraction for the highly influential zones that were dropped for the training of the model show the largest errors. Figure 11 visualizes spatially the prediction error per zone.

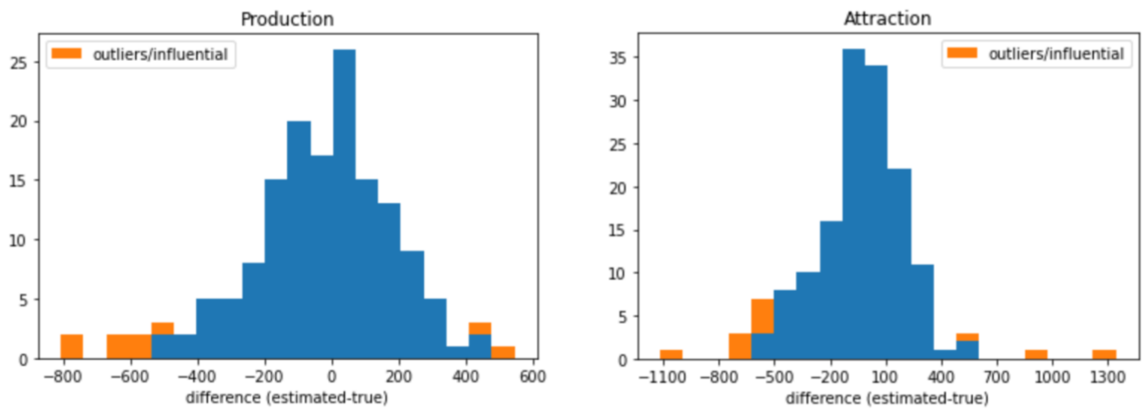


Figure 10: Distribution of prediction errors for production (a) and attraction (b)

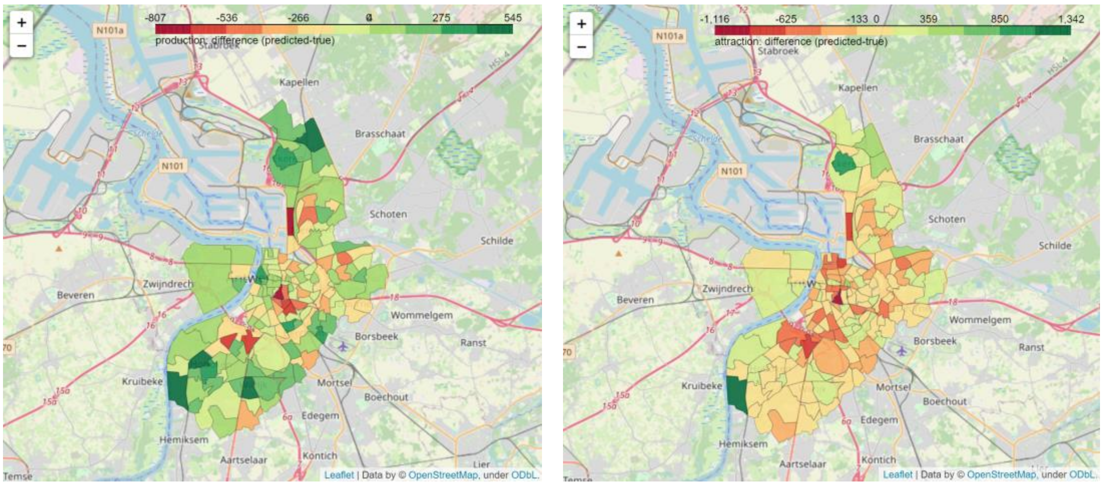


Figure 11: Difference in predicted and true production (a) and attraction (b) per zone

Table 4 and

Attraction	Number of zones	Proportion of total attraction [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 250	19	2.43	117.75	143.63	25.88	72.82	102.78	75.33
250-500	32	13.51	389.11	502.32	113.21	160.42	208.73	43.50
500-750	42	28.79	631.91	602.27	-29.64	174.78	218.21	27.31
750-1000	27	25.18	859.50	721.37	-138.13	200.34	253.84	23.39
1000-1250	17	20.65	1119.77	1038.83	-80.94	110.48	141.32	9.87
1250-1500	4	5.77	1330.47	1102.07	-228.40	228.40	299.85	16.76
1500-1750	1	1.73	1592.57	1573.13	-19.45	19.45	19.45	1.22
>= 1750	1	1.93	1783.46	1394.29	-389.17	389.17	389.17	21.82
Total	143	100.00	644.54	619.66	-24.88	157.11	207.98	33.69

report on the performance in different classes representing the full range of production and attraction values, respectively (excluding the outliers). They report on different error measures including the bias (the difference in predicted mean and true mean of zonal production and attraction), the mean absolute error (MAE), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE). For each class, it is reported how many zones are included in the associated production or attraction range and which proportion of the total demand is produced or attracted by these zones.

Table 4: Performance production model

Production	Number of zones	Proportion of total production [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 250	20	2.14	100.71	131.66	30.95	68.89	114.29	87.83
250-500	32	13.02	383.16	426.90	43.74	112.86	148.35	30.49
500-750	41	26.21	602.15	596.02	-6.13	154.60	178.41	26.03
750-1000	22	19.62	839.78	824.55	-15.23	177.51	217.89	20.74
1000-1250	19	22.17	1098.73	1024.84	-73.89	186.59	220.19	17.15
1250-1500	8	11.44	1347.19	1164.50	-182.69	199.80	259.37	14.96
1500-1750	2	3.48	1638.79	1351.26	-287.54	287.54	287.54	17.61
>= 1750	1	1.92	1807.83	1334.70	-473.13	473.13	473.13	26.17
Total	145	100.00	649.50	632.39	-17.11	147.76	188.71	32.46

Table 5: Performance attraction model

Attraction	Number of zones	Proportion of total attraction [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 250	19	2.43	117.75	143.63	25.88	72.82	102.78	75.33
250-500	32	13.51	389.11	502.32	113.21	160.42	208.73	43.50
500-750	42	28.79	631.91	602.27	-29.64	174.78	218.21	27.31
750-1000	27	25.18	859.50	721.37	-138.13	200.34	253.84	23.39
1000-1250	17	20.65	1119.77	1038.83	-80.94	110.48	141.32	9.87
1250-1500	4	5.77	1330.47	1102.07	-228.40	228.40	299.85	16.76
1500-1750	1	1.73	1592.57	1573.13	-19.45	19.45	19.45	1.22
>= 1750	1	1.93	1783.46	1394.29	-389.17	389.17	389.17	21.82
Total	143	100.00	644.54	619.66	-24.88	157.11	207.98	33.69

Trip Distribution

To evaluate the performance of the trip distribution model itself (and not the performance of the combined trip generation and distribution model which is discussed further in the report), first, the actual true production and attraction values are used as inputs for the model. The performance is visualized in Figure 12. The prediction error slightly increases for OD pairs with a larger number of OD trips. Moreover, it is clear most of them are underestimated. Overall, the R^2 value between the estimated and true OD values is equal to 0.765.

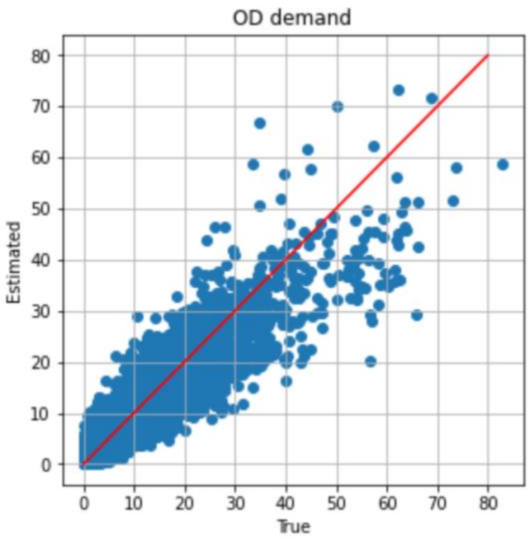


Figure 12: True and estimated number of trips per OD (starting from true zonal production and attraction)

Figure 13 visualizes the trip cost distribution derived from the true and estimated OD matrices. Looking at these graphs, it is clear the model is able to transfer a large part of the inherent structure of the true OD matrix to the estimated one. From this plot, one might expect that the number of trips made between zones located at a distance of 0-3 minutes will be underestimated.

Table 6 provides more detailed information on the performance of the distribution model over the full range of number of trips. It reports on the bias, the mean absolute error (MAE), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE). Looking at the bias metric, the conclusion made above that larger OD values are underestimated is confirmed. For the MAE and RMSE, similar trends are observable. The MAPE metric shows there is an error of 20-30%, except for the first class which is merely a consequence of the metric structure that gets strongly biased for errors on small values. Interesting to notice is that there is an

overall overestimation for OD pairs with a number of trips smaller than 5. This is partly the result of zero cells in the true OD matrix. In the estimated matrix, these will always get a value different from 0 if the shortest path travel time is larger than 0 and zonal production and attraction are not 0.
Figure 13 visualizes the trip cost distribution derived from the true and estimated OD matrices. Looking at these graphs, it is clear the model is able to transfer a large part of the inherent structure of the true OD matrix to the estimated one. From this plot, one might expect that the number of trips made between zones located at a distance of 0-3 minutes will be underestimated.

Table 6: Performance distribution model (starting from true zonal production and attraction)

OD	Number of OD pairs	Proportion of total demand [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 5	17089	25.84	1.57	1.92	0.35	0.90	1.31	77.19
5-10	3703	25.04	7.03	6.93	-0.10	1.95	2.50	28.18
10-15	1372	16.03	12.15	11.54	-0.61	2.76	3.50	22.82
15-20	601	9.93	17.19	15.49	-1.69	3.80	4.64	22.03
20-25	317	6.78	22.24	20.09	-2.15	4.74	5.81	21.36
25-30	189	4.93	27.10	23.00	-4.10	6.62	7.90	24.34
30-35	109	3.39	32.33	27.39	-4.94	6.82	8.83	21.01
35-40	66	2.35	37.06	30.99	-6.06	7.68	9.51	20.57
40-45	41	1.67	42.35	35.00	-7.34	9.42	11.48	22.17
45-50	18	0.82	47.42	37.95	-9.48	9.48	11.31	20.12
50-55	20	1.02	53.13	39.17	-13.96	15.96	16.44	30.07
55-60	17	0.94	57.59	39.45	-18.14	18.74	20.56	32.51
60-65	13	0.78	62.36	46.08	-16.28	17.99	18.98	28.90
65-70	4	0.26	66.73	48.66	-18.07	19.62	23.11	29.68
70-75	2	0.14	73.39	54.86	-18.53	18.53	18.73	25.27
75-80	0	0.00	nan	nan	nan	nan	nan	nan
>= 80	1	0.08	82.93	58.90	-24.03	24.03	24.03	28.97
Total	23562	100.00	4.41	4.41	0.00	1.45	2.50	59.75

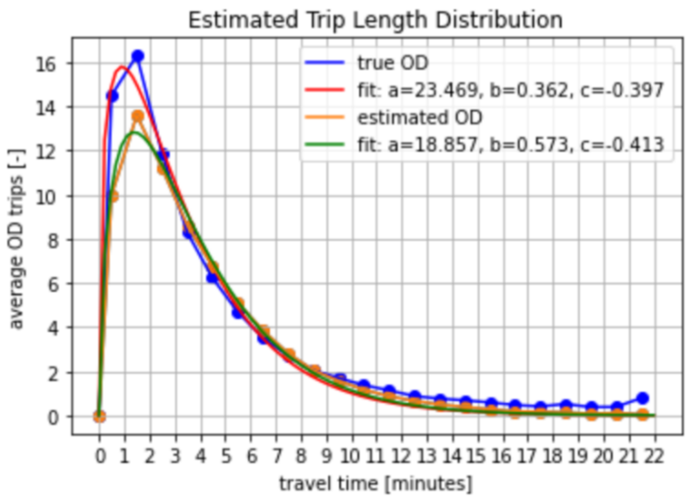


Figure 13: Calibrated trip cost distribution from true and estimated OD matrices

In our demand generation method depicted in Figure 1, the trip generation and trip distribution are sequentially performed. Thus, the zonal production and attraction estimated by the production and attraction models are used as inputs for the distribution model. This means that errors are accumulated over the two steps. The performance of sequentially performing these two steps is discussed here. To be able to run the distribution model with the predicted zonal production and attraction (which requires total production and attraction to be equal), total production and attraction are balanced. It is chosen to apply a correction factor to the estimated attraction values as the production model has a better performance.

Figure 14 compares the true and the predicted values. Some OD cells are clearly overestimated. The overall R^2 value is -0.087. This means that the linear relationship between the true and predicted values is rather weak and/or is biased by outliers (indeed, some OD-cells are predicted as being exceptionally high (above 75), while this is not correct according to the reference data).

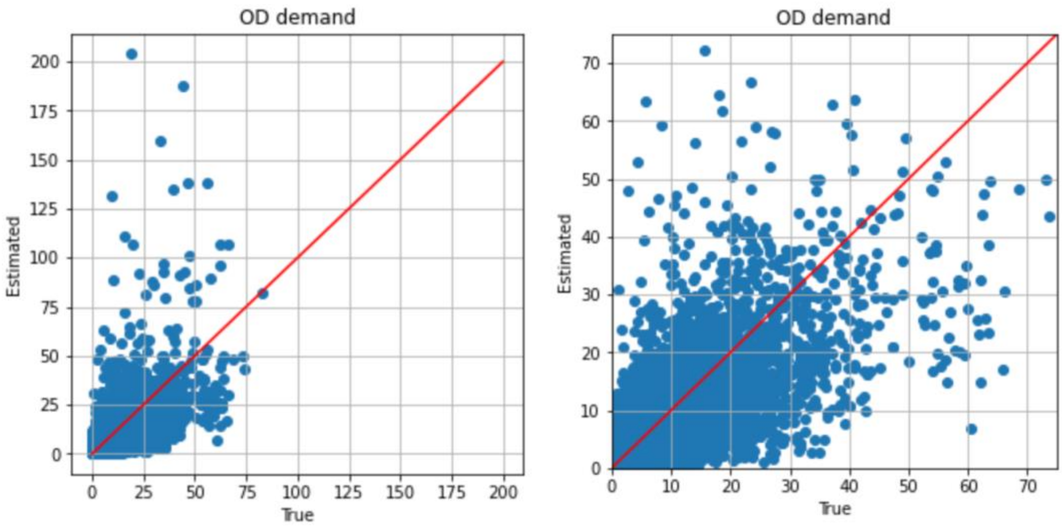


Figure 14: True and estimated number of trips per OD pair (starting from estimated zonal production and attraction) (a): full result; (b): zoom excluding estimates above 75 trips

Table 7 presents the performance for the different OD ranges. Overall, the number of trips is underestimated. This is of-course the result of total production and attraction being underestimated by the trip generation models. Most classes have MAPE between 40 and 55%. This may at first seem a disappointingly large error. However, one needs to bear in mind that the finer the level of disaggregation (here: OD-cells where before we were considering zonal demand/attraction corresponding to row/column sums of OD-cells), the harder it gets to make accurate predictions as aggregates always have smaller variance that its disaggregate components. Moreover, considering the very limited POI information that we use as input to our procedure, it is actually remarkable that so much structure of aggregate and disaggregate OD-demand can be captured. Obviously, further refinement of the POI-driven method and inclusion of other data may and will further improve these results.

Table 7: Performance distribution model (starting from estimated zonal production and attraction)

OD	Number of OD pairs	Proportion of total demand [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 5	17089	25.84	1.57	1.99	0.42	1.19	1.94	99.65
5-10	3703	25.04	7.03	6.21	-0.82	3.21	4.75	46.08
10-15	1372	16.03	12.15	10.08	-2.06	5.27	7.00	43.61
15-20	601	9.93	17.19	14.21	-2.98	7.64	12.81	44.26
20-25	317	6.78	22.24	17.76	-4.48	9.73	12.10	43.81
25-30	189	4.93	27.10	20.47	-6.63	11.45	14.43	42.15
30-35	109	3.39	32.33	23.86	-8.47	14.94	20.86	45.89
35-40	66	2.35	37.06	27.17	-9.89	16.55	21.52	44.50
40-45	41	1.67	42.35	35.57	-6.78	21.10	30.60	49.51
45-50	18	0.82	47.42	49.96	2.54	22.21	31.07	47.26
50-55	20	1.02	53.13	37.54	-15.59	21.91	23.98	41.48
55-60	17	0.94	57.59	37.06	-20.53	34.01	37.13	59.20
60-65	13	0.78	62.36	41.11	-21.25	33.33	35.38	53.63
65-70	4	0.26	66.73	50.73	-16.01	36.48	37.94	54.92
70-75	2	0.14	73.39	46.68	-26.71	26.71	26.95	36.37
75-80	0	0.00	nan	nan	nan	nan	nan	nan
>= 80	1	0.08	82.93	81.96	-0.97	0.97	0.97	1.17
Total	23562	100.00	4.41	4.16	-0.26	2.33	5.01	81.17

Figure 15 compares the trip cost distribution calibrated on the true and estimated OD matrices. This graph shows that after performing trip generation and trip distribution sequentially, the resulting OD matrix possess a similar structure as the OD matrix that is considered as ground truth.

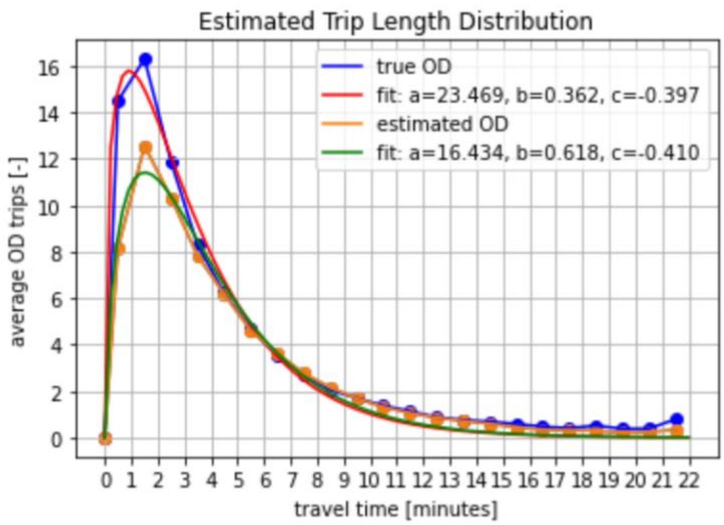


Figure 15: Calibrated trip cost distribution from true and estimated (starting from estimated zonal production and attraction) OD matrices

The accumulation of errors can be explained as follows. First, the estimated zonal production and attraction is not equal to the actual values; this is partly because the POI layer used to generate production and attraction is imperfect (see various pragmatic POI-processing choices in POI-extraction and pre-processing); moreover, the POIs only explained part of the variation in production and attraction both for the zones that roughly followed the trend and a fortiori for the outlier zones. Secondly, as production and attraction were modelled separately, the total number of produced trips and attracted trips was not the same and needed to be balanced, introducing additional errors in the row and column totals of the trip distribution model. The consequent Furness distribution distributes the production/attraction errors over the OD matrix cells, even if the distribution model had been perfect. Finally, the distribution itself proved imperfect and introduces further error. Also here, the cause of these errors is a mixture of the simple model (only 3 parameters and just the travel impedance as the only explanatory variable) with errors in its inputs (the impedance was coarsely approximated by the free flow time neglecting intersection delays).

Improvements in model accuracy thus need to be sought in all steps: both in more accurate input data, in inclusion of more input data containing complementary information on trip demand and distribution, and in more refined model structures. Also, calibrating the trip generation step and trip distribution step simultaneously might improve the model performance. One should not disregard, however, that not all perceived deviations from the MOW reference OD-matrix are necessarily modeling errors. The reference itself is, after all, not a direct and perfect observation of trips in the region, but it is the result of a demand generation exercise. No matter how much data was used and how experienced and skillful the developers of the MOW data are, any model inevitably contains error. Moreover, the OD-matrix probably underwent further fine-tuning aimed at improving the fit to data of subsequent modeling steps (route assignment), a 'matrix calibration' process that is well-known for its risk of introducing biases into the OD-matrix structure. Possibly, the 'outliers' that we observed in our model fit may be partly explained by such biases in the reference data. While looking for ways to improve the outcome of our demand generation tool, this possibility should not be disregarded, even though it should not be used as an excuse for imperfections either.

Nevertheless, this first version of the demand-generation model is a proof of concept showing that large parts of demand can indeed be explained and generated from widely available open data.

Ghent

How well can these models be transferred to estimated production and attraction or generate an OD matrix for other cities in Flanders? To study the transferability of calibrated parameters, a case study for Ghent, Flanders has been performed. The study area is visualized in Figure 16. Similar to Antwerp, the harbor zones (grey) were dropped from the study area. This is because the production and attraction model were not calibrated for estimating demand generated by a harbor as these zones possess specific characteristics different from the mixed land-use in most of the zones.

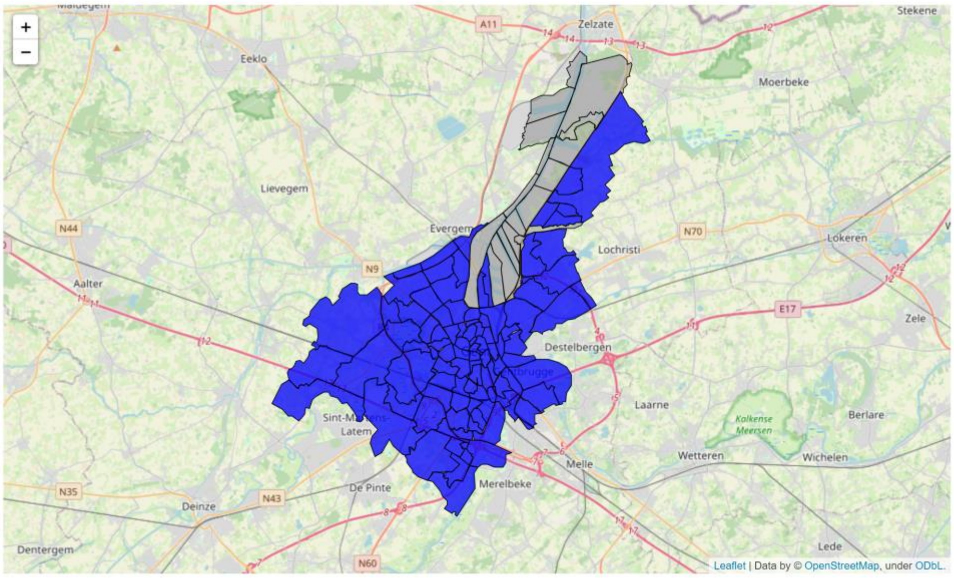


Figure 16: Ghent study area

Trip Generation

As the model is calibrated for the interzonal car traffic in the morning peak (5am until 11am), the model performance is compared with the true production and attraction values calculated from the OD matrix extracted from the MOW dataset representing interzonal car traffic in the morning peak in Ghent. The zonal production and attraction are visualized in Figure 17.

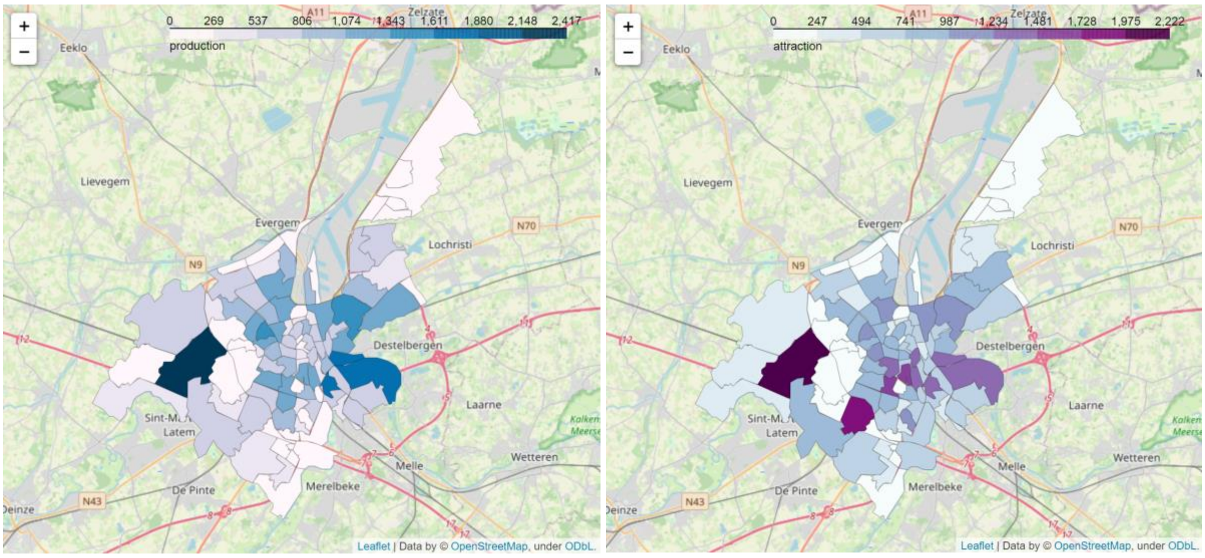


Figure 17: Case study Ghent: (a) Zonal production (b) Zonal attraction

The performance of applying the production and attraction model to Ghent is discussed next. Figure 18 compares the true zonal production and attraction with the estimated production and attraction of each zone. The R^2 values representing the correlation between the predicted and true values are 0.677 for production and 0.247 for attraction.

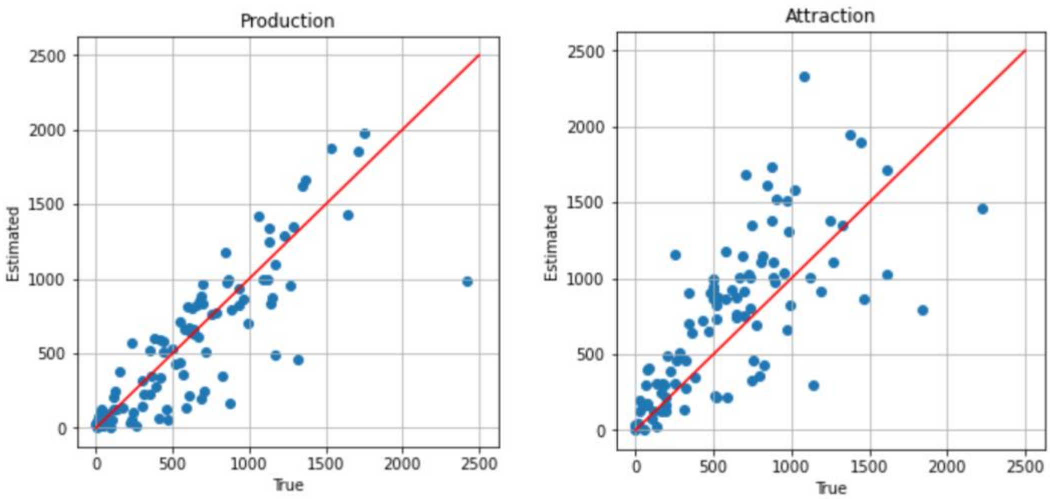


Figure 18: Case study Ghent: True and estimated production (a) and attraction (b) values

In the plot associated with production, more points are below the 45° line which means production is in general slightly underestimated. The inverse is true for attraction. Here, more points are above the 45° line meaning zonal attraction will in general be overestimated. Both trends are confirmed by respectively comparing the total produced trips (60372) with the total predicted production (55622 or +8.5% error) and the total attracted trips (60372) with the total predicted attraction (73902 or -18.3% error) over all zones.
A similar observation can be made from Figure 19, which represents the histogram of the prediction errors for production as well as attraction. Analyzing the graphs shows that most of the zonal production and attraction is predicted with relative small errors, and only a handfull of zones have a large error.

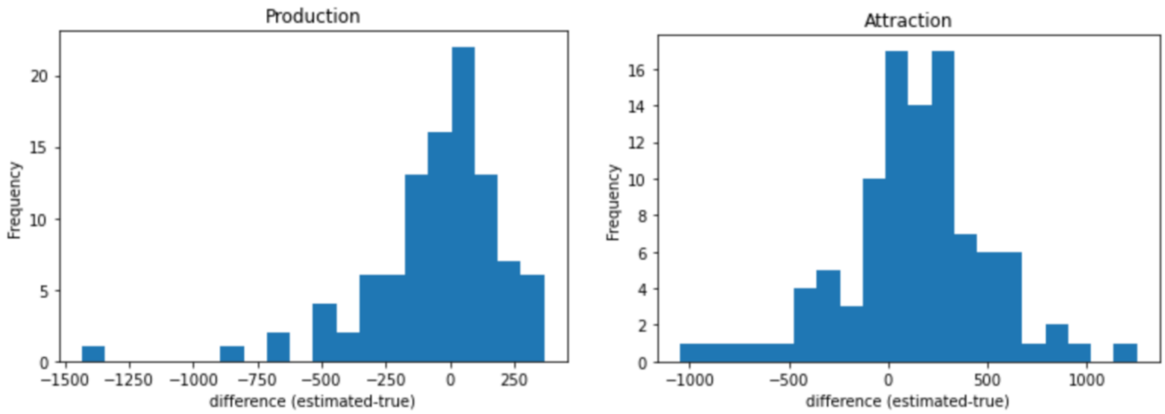


Figure 19: Case study Ghent: Prediction errors of production (a) and attraction (b)

Figure 20 gives a better view on for which zones the model was unable to predict production and attraction reasonably well. While comparing Figure 20 with Figure 17, interesting to notice is that the large errors are mainly made for the zones that really stand out in Figure 17, having a significantly higher amount of trips compared to the other zones. This means that either we either fail to acknowledge an important production/attraction factor that exists in reality, or there exists a bias in the reference data (or part of both).

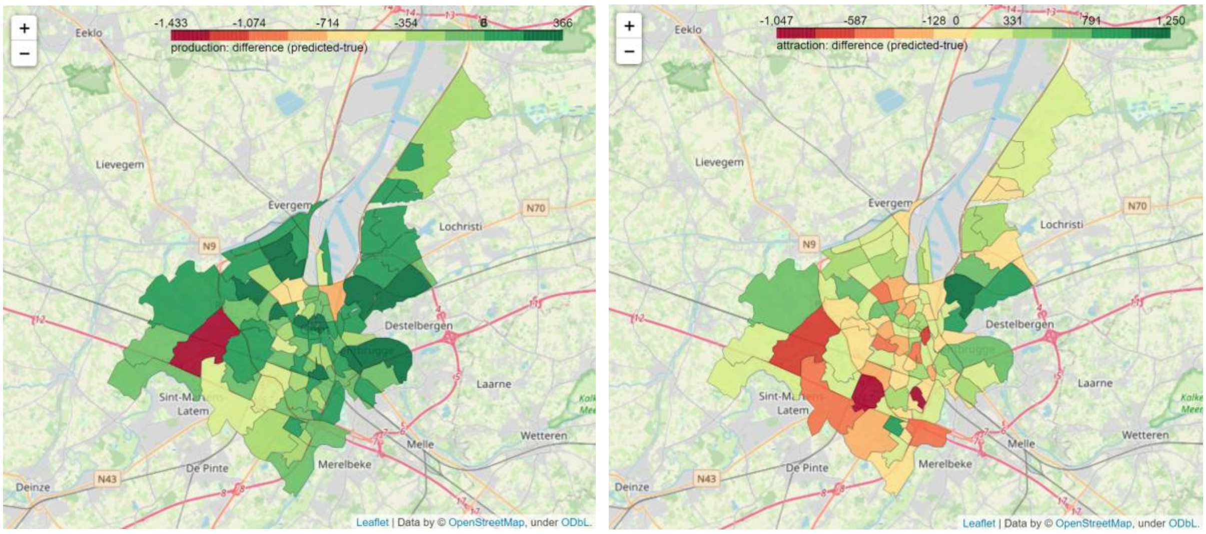


Figure 20: Case study Ghent: Difference in predicted and true production (a) and attraction (b) per zone

Table 8 and

Table 9 give more insight into the overall performance of the production and attraction model. The reported error measures include the bias, the mean absolute error (MAE), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE). Additionally, the tables split these measures over different classes covering the full range of production and attraction values.

Table 8: Case study Ghent: Performance production model

Production	Number of zones	Proportion of total production [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 250	28	3.99	86.03	104.23	18.21	74.88	108.39	193.11
250-500	16	10.07	380.05	310.29	-69.76	168.42	203.22	43.83
500-750	23	23.82	625.17	593.29	-31.88	183.04	230.64	28.84
750-1000	12	17.38	874.57	777.47	-97.11	199.70	288.66	22.80
1000-1250	10	18.84	1137.57	1059.42	-78.15	230.72	292.45	20.36
1250-1500	5	10.89	1315.19	1208.94	-106.25	360.32	446.17	27.37
1500-1750	3	8.09	1628.79	1722.46	93.67	235.59	249.78	14.72
1750-2000	1	2.91	1754.29	1974.55	220.26	220.26	220.26	12.56
2000-2250	0	0.00	nan	nan	nan	nan	nan	nan
>= 2250	1	4.00	2416.70	983.29	-1433.41	1433.41	1433.41	59.31
Total	99	100.00	609.82	561.84	-47.98	180.48	272.55	73.36

Table 9: Case study Ghent: Performance attraction model

Attraction	Number of zones	Proportion of total attraction [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 250	26	4.58	106.29	190.03	83.73	109.00	143.57	146.22
250-500	17	10.42	370.18	651.18	281.00	309.98	378.01	87.00
500-750	23	24.09	632.40	841.04	208.63	328.17	382.04	52.54
750-1000	18	26.18	878.12	1048.48	170.36	358.34	422.14	41.14
1000-1250	6	11.25	1132.30	1253.53	121.22	528.79	670.29	48.05
1250-1500	5	11.39	1375.49	1431.47	55.98	359.71	428.65	25.51
1500-1750	2	5.35	1614.81	1371.41	-243.40	342.05	419.81	21.20
1750-2000	1	3.05	1841.68	794.77	-1046.91	1046.91	1046.91	56.85
>= 2000	1	3.68	2221.78	1458.68	-763.10	763.10	763.10	34.35
Total	99	100.00	609.82	746.49	136.66	298.66	391.51	77.89

Trip distribution

Similar as for the trip generation step, the transferability of the calibrated parameters in the trip distribution step is evaluated. This is first tested using the true zonal production and attraction in Ghent. In this way, solely the performance of using the calibrated deterrence function of Antwerp for Ghent is analyzed and it is not influenced by the errors made in the trip generation step. The performance of combining trip generation and distribution is discussed afterwards.

Figure 21 shows the relationship between the true and estimated number of trips per OD pair. It has a R^2 value of 0.682, indicating a significant part of the variation in the data is captured by the model. Table 10 provides more insights on the performance over the full range of OD values. Most classes exhibit a MAPE between 10 and 25%.

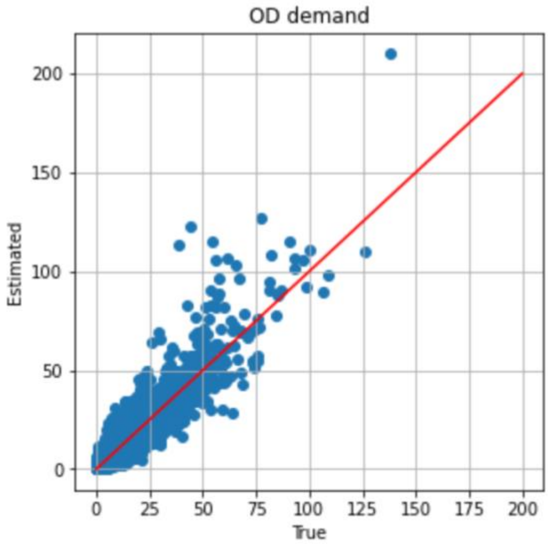


Figure 21: Case study Ghent: True and estimated number of trips per OD

Table 10: Case study Ghent: Performance distribution model (starting from true zonal production and attraction)

OD	Number of OD pairs	Proportion of total demand [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 15	8579	47.39	3.33	3.28	-0.05	1.31	2.20	53.78
15-30	781	26.61	20.57	20.34	-0.23	4.87	6.54	23.82
30-45	205	12.29	36.20	37.27	1.07	7.28	11.59	19.95
45-60	90	7.64	51.28	54.84	3.56	11.33	15.99	21.82
60-75	25	2.74	66.08	64.47	-1.61	15.48	19.49	23.59
75-90	12	1.58	79.60	83.89	4.29	13.50	19.02	17.19
90-105	6	0.95	95.47	105.38	9.91	12.11	13.47	12.86
105-120	2	0.36	107.88	93.54	-14.34	14.34	14.69	13.32
120-135	1	0.21	126.18	109.61	-16.56	16.56	16.56	13.13
>= 135	1	0.23	138.33	209.97	71.65	71.65	71.65	51.80
Total	9702	100.00	6.22	6.22	0.00	1.89	3.88	48.94

Of course, running the distribution model with the zonal production and attraction estimated by the trip generation model reveals a worse performance. Figure 22 visualizes the correlation between the estimated and true number of produced and attracted trips when performing trip distribution with the estimated production and attraction. The R^2 is equal to -0.822. Table 11 shows the performance over the full range of OD values. Looking at the MAPE, it is clear prediction errors increase from 10-25% to 40-55%, for most OD ranges.

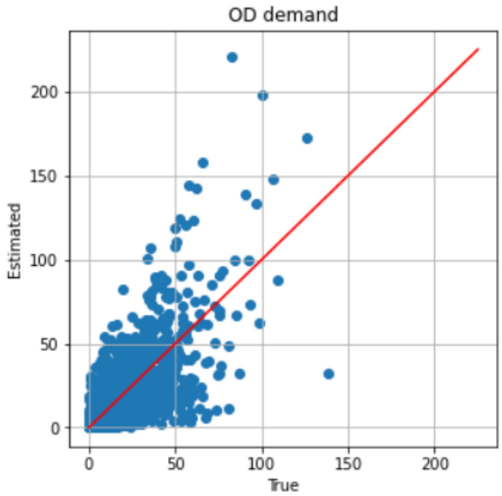


Figure 22: True and estimated number of OD trips (starting from estimated zonal production and attraction)

Table 11: Case study Ghent: Performance distribution model (starting from estimated zonal production and attraction)

OD	Number of OD pairs	Proportion of total demand [%]	True mean	Predicted mean	Bias	MAE	RMSE	MAPE [%]
< 15	8579	47.39	3.33	3.35	0.01	2.22	3.94	86.98
15-30	781	26.61	20.57	16.96	-3.61	9.39	11.69	46.04
30-45	205	12.29	36.20	30.98	-5.22	19.17	22.57	53.04
45-60	90	7.64	51.28	42.93	-8.35	25.88	31.53	50.00
60-75	25	2.74	66.08	56.32	-9.76	34.09	42.54	51.95
75-90	12	1.58	79.60	72.51	-7.09	38.03	52.09	47.11
90-105	6	0.95	95.47	117.50	22.04	41.07	50.12	42.45
105-120	2	0.36	107.88	117.95	10.08	30.77	32.38	28.62
120-135	1	0.21	126.18	172.58	46.40	46.40	46.40	36.77
>= 135	1	0.23	138.33	31.89	-106.43	106.43	106.43	76.94
Total	9702	100.00	6.22	5.73	-0.49	3.55	7.47	80.86

Athens

To demonstrate a potential application of the demand-generation tool, an initial OD matrix for the city of Athens is estimated. The tool can generate an OD matrix for any definition of study area and zones. The considered study area and the used zoning are visualized in Figure 23.

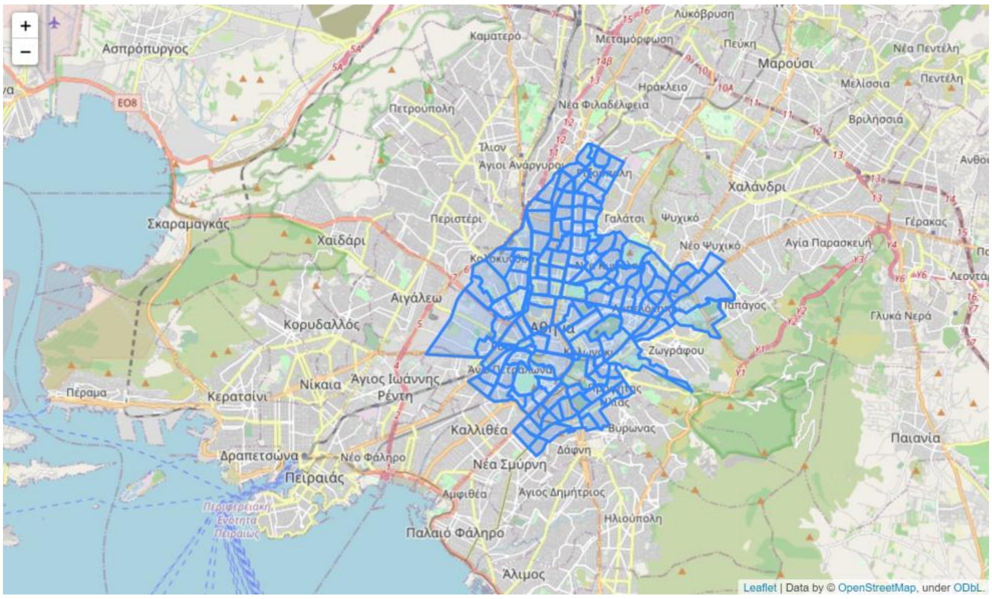


Figure 23: Study area and zoning Athens

Trip generation

Applying the calibrated production and attraction model to Athens generates the results visualized in Figure 24 and Figure 25. These results represent the interzonal travel demand by car in the morning peak. The estimated production and attraction per km^2 per zone are also displayed. This removes the influence of the area of a zone on the number of trips. Apparently the more centrally located zones in the region of Athens, representing the city of Athens, produce and attract more trips per km^2 compared to the more outer-located zones. This is in line with what could be expected in real life. However, the extreme difference in production/attraction between zones is, in general, undesirable in transport models; because there exist multiple orders of magnitude differences between the zones, correction of (relatively small) errors on the larger ones could come at the cost of completely distorting smaller ones (extreme corrections in relative terms, however, in absolute terms possibly still be quite small). In other words: based on this first result, it is recommendable to revise the zoning of this model and make them more homogeneous in terms of total production/attraction; this means refinement of the busy zones and aggregation of the quieter ones.

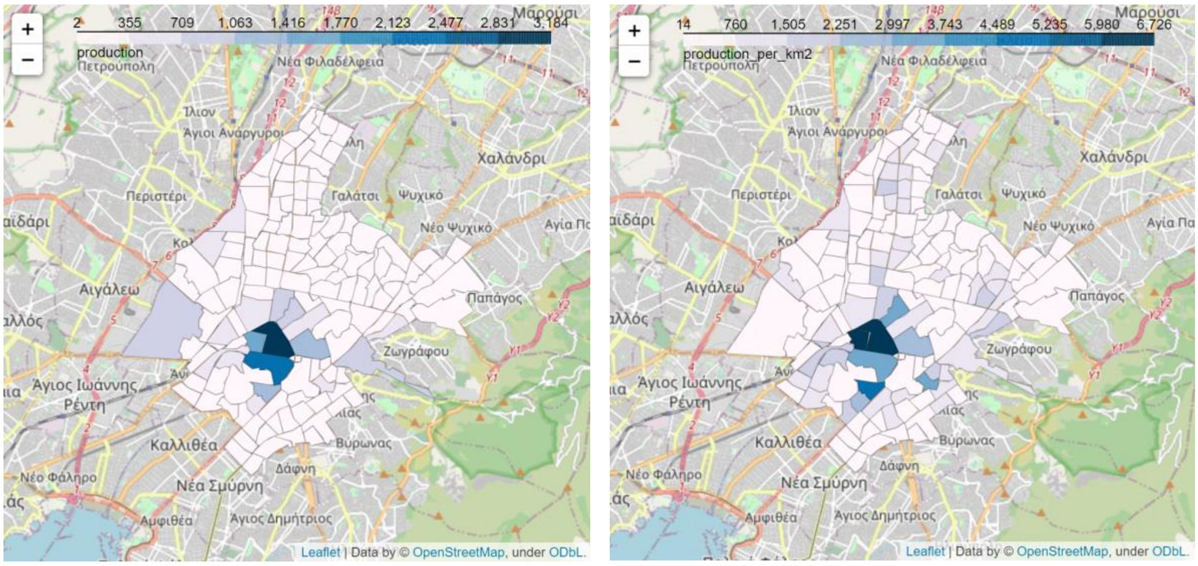


Figure 24: Case study Athens: (a) Predicted total production and (b) production per km²

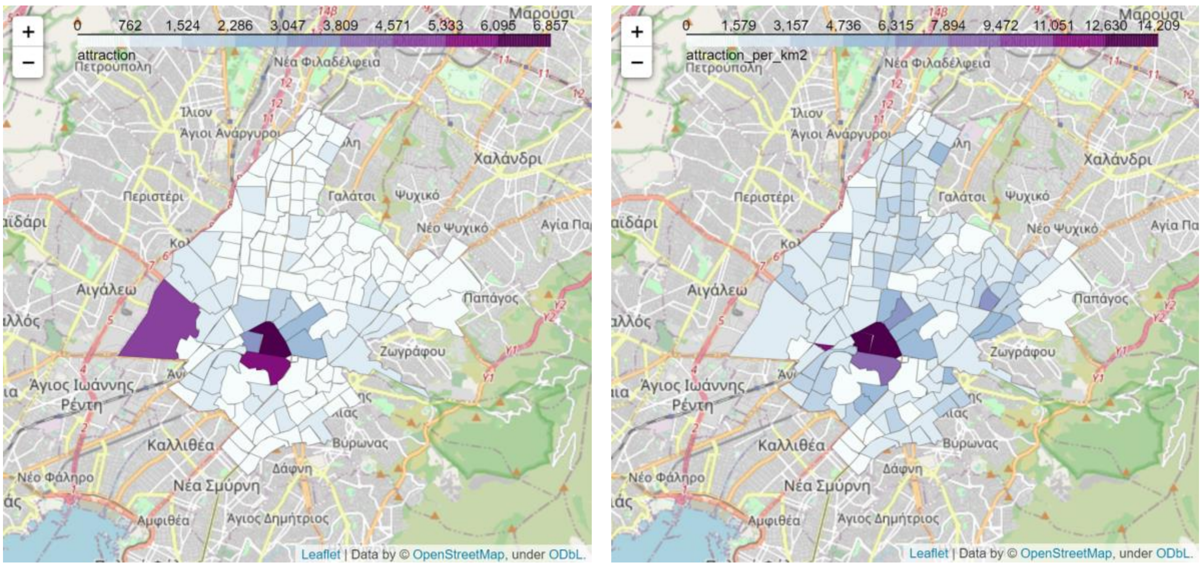


Figure 25: Case study Athens: (a) Predicted total attraction and (b) attraction per km²

The total estimated production and attraction equal 31048 and 105468, respectively. The estimated attraction is more than 3 times as large as the total estimated production. As a comparison: total production and attraction in Antwerp was 103976 (hence: 3x larger production, ~similar attraction), while the total zone area for the case study of Antwerp (94 km^2) is about 2.5 times larger than that of Athens (38 km^2). This may indicate that production may be reasonably estimated while we overestimated attraction. The comparison of these areas, however, does not consider how dense these areas are populated. Comparing the production and attraction per km^2 in Antwerp (Figure 26) and Athens (Figure 24 and Figure 25) provides additional insights. The estimated number of produced trips per km^2 in Athens and Antwerp show the same order of magnitude. Nevertheless, there are significantly fewer zones with a large production than there exist in Antwerp. For attraction, these estimations per km^2 show values up to twice as large as in Antwerp, although these peak attraction values are limited to only two zones. The other zones in Athens show values more in the range of the observed values in the city center of Antwerp, but the surrounding satellite towns clearly attract less traffic. Hence, while the Antwerp study area is a mix of high-density inner city and medium density satellites and the entire Athens study area is more high-density inner city, the larger attraction of Athens could indeed correspond to reality. In that case, however, the unbalance between production and attraction shows that the Athens study area may have been defined too narrowly, missing quite some important production zones that are now external. This is (together with the above-mentioned unbalanced sizes of the zones) another reason for reconsidering the Athens study area and zoning before proceeding to build a full traffic model.

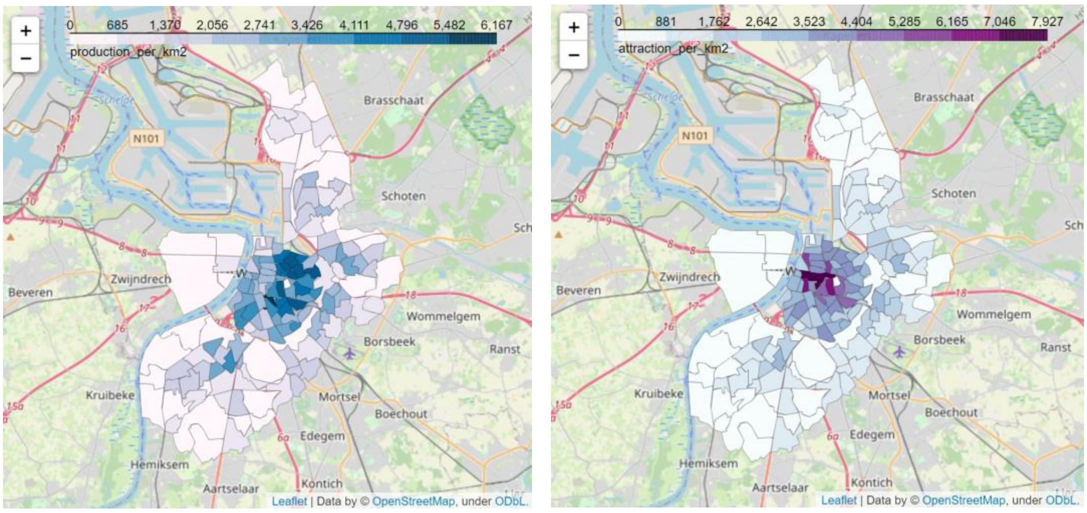
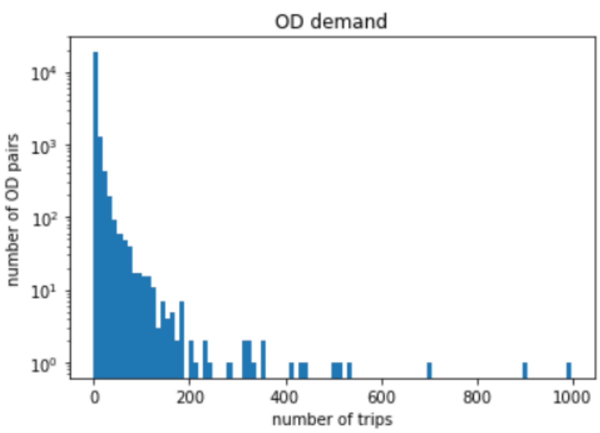


Figure 26: Case study Antwerp: (a) production and (b) attraction per km²

Trip distribution

Because there is larger confidence in the estimated zonal attraction, it is chosen to balance total production towards the total number of attracted trips. These balanced production and attraction values serve as input to generate the OD matrix. The calibrated trip cost distribution of Antwerp is used as deterrence function and the Furness iteration process is applied.

This results in an OD matrix for the city of Athens. The generated OD matrix is represented by the distribution of trips visualized in Figure 27.



OD	Number of OD pairs	Proportion of total demand [%]	Mean	Std
< 10	18352	34.13	1.96	2.21
10-20	1264	16.89	14.09	2.84
20-30	422	9.75	24.37	3.03
30-40	190	6.19	34.38	2.89
40-50	93	3.94	44.66	2.93
50-60	59	3.07	54.85	2.83
60-70	49	3.04	65.42	2.71
70-80	38	2.68	74.37	3.02
80-90	17	1.37	84.84	3.10
90-100	16	1.45	95.58	2.85
100-110	17	1.68	104.42	3.01
>= 110	14	1.53	114.97	2.51
Total	20592	100.00	5.12	19.01

Figure 27: Distribution of OD trips

Given the errors observed while transferring the calibrated demand generation for Antwerp to Ghent, one can expect larger differences between Athens and Antwerp than between Ghent and Antwerp. Indeed, not only are there larger cultural and economic differences, so that production and attraction factors per POI unit and distribution characteristics are less similar in Athens as compared to Ghent. In addition, one can also expect larger differences in the data sources and coding habits with which the OSM databases have been filled, and thus the validity of the pragmatic decisions in the POI extraction and pre-processing procedure may be less for Athens than it is for Ghent.

Nevertheless, despite its inevitable shortcomings, the provided OD-matrix of Athens probably explains a modest but important part of the variation of OD-demand and can be a reasonable starting point for further refinements and what-if scenarios.

B.5. Discussion

As we learned from the case studies, including the transfer of Antwerp-calibrated models to Ghent and Athens, there are some important aspects to keep in mind when transferring the model calibrated for a certain city or region to another one. This is sketched here to convey the complexity of demand modelling and the inherent difficulty of obtaining valid results, which of course motivates the need for case-specific calibration.

Travel behavior is for a large part determined by land use and spatial planning practices in a region and might therefore also vary between regions. The developed models were calibrated for a typical Flemish context, in this case for the city of Antwerp, a large metropolitan area. Therefore, one should keep in mind that applying the calibrated parameters for another sized city within another context might not give proper results.

As OSM is a VGI system, the generated datasets might vary widely between regions and be highly dependent on the practices of local contributors and the source data that they dispose of. Of course, this will also influence the results. Including other types of open-source data that are more consistent over different regions (e.g. census data, geographic statistics such as population density) might improve the transferability of the models to other cities.

In this research, no external demand is considered. The calibrated coefficients and parameters in the production and attraction models and the calibrated trip cost distribution are a result of the considered extent of the study area for Antwerp. Increasing the study area would have increased the production and attraction of each zone, in turn increasing the trip rates calibrated in the production and attraction model. Moreover, this would also mean there are trips that are performed over a larger distance, changing the tail of the trip cost distribution. For now, transferring the model to a case study with a study area comparable in size will do. Nevertheless, future research should address the distinction between study area zones and external zones; each with their way of extracting and aggregating POI information (and network data).

B.6. Conclusion

We presented a first version of a demand-generating tool allowing us to estimate travel demand quickly and easily for a region/city based on information available in OSM without making use of expensive and time-consuming travel surveys. The developed models showed to be able to explain large parts of the relationship between travel demand and the built environment and capture most the underlying characteristics in travel behavior.

Aside from the application demonstrated in this report, the models developed can bring added value for other use cases too, e.g. for calibrating a traffic model. Current practice tweaks individual OD cells to make sure traffic flows resulting from assigning the OD matrix align with observed traffic counts. Deriving production and attraction models from an existing OD matrix with this tool would allow calibrating the trip rate coefficients of these models instead of individual OD cells. From a methodological standpoint, this is preferable as the trip rate coefficients are actual parameters whereas the OD matrix is an intermediate result of the 4-steps model. Changing the parameters would thus preserve the spatial structure of demand, just translate it differently into trips, while the existing fine-tuning practice directly on OD-cells distorts the structure of the matrix and is more likely to lead to overfitting. The latter might reproduce the reference case to which it was calibrated slightly better, however, would perform much worse predictions because of its inherent bias.

Another envisioned application is the generation of more disaggregate results for travel demand, and more general: changes to the currently existing demand (e.g. in what-if scenarios). Currently, the traditional 4-steps model uses the notion of traffic analysis zones. This approach, however, discards intrazonal traffic completely. Moreover, zonal demand is typically allocated to zone centroids, i.e., hypothetical gravity points of the zone from which it is assigned via artificial connectors to the network. This means the routing behavior of interzonal traffic within their origin and destination zones is disregarded, or at best very poorly modelled. Nevertheless, in recent years, increasingly more research questions, such as the proper modelling of demand responsive transport systems, require more detailed information on the origin and destination location of trips. Demand-generating tools can help disaggregating in a way consistent with land use the travel demand into smaller zones or even going towards demand on POI-level. This could be in the form of splitting the demand of a zone into multiple smaller zones according to (demand-generating-potential weighted) POIs density or hotspots of POIs in an area. Ultimately, trips would be modelled on POI-level which would remove the notion of zoning and thus, the difference in inter- and intrazonal trips.

Likewise, the method could support extrapolating existing demand to future what-if scenarios. Policy targeted to mobility management of specific activities (e.g. home-work or home-school commuting, or leisure-related trips) might affect certain POI types more than others; the tool would translate this to zones proportional to the corresponding POI density of the affected POI types. Also, planned changes of land use can be transformed into demand changes using this tool.

In conclusion, as the first iteration of a long-term research line, this study reveals promising results that show this research is an interesting path to further explore and develop. There are many ways in which the demand-generating tool can be further enhanced; some have been briefly discussed. We could have worked more to make each individual step more accurate before proceeding to the next stage of the chain. However, completing the chain even with rather coarse model design choices in each step has the advantage that now, before engaging in specific refinements, we can use the complete tool for sensitivity analysis that allows anticipating how important such improvement might be for the end result. This is very important when prioritizing potential next steps. At the time of writing, such sensitivity analysis had not been performed yet.

B.7. Appendices

Appendix B1

Table 12: Selection of attribute and values for data extraction from OSM

landuse	building	amenity	leisure
residential	apartments	kindergarten	fitness_centre
commercial	dormitory	school	park
retail	house	university	playground
industrial	semidetached_house	college	recreation_ground
recreation_ground	terrace	library	sports_centre
	residential	arts_centre	sports_hall
	farm	cinema	stadium
	detached	community_centre	
	cathedral	conference_centre	
	chapel	events_venue	
	church	nightclub	
	monastery	theatre	
	mosque	bank	
	presbytery	baby_hatch	
	religious	clinic	
	synagogue	dentists	
	temple	doctors	
	kindergarten	hospital	
	school	nursing_home	
	university	pharmacy	
	college	social_facility	
	hospital	veterinary	
	civic	courthouse	
	fire_station	embassy	
	government	fire_station	
	commercial	police	
	retail	post_depot	
	industrial	post_office	
	kiosk	prison	
	office	townhall	
	supermarket	bar	
	warehouse	biergarten	
	stadium	café	
	sports_hall	fast_food	
	yes	food_court	
		ice_cream	
		pub	
		restaurant	

Appendix B2

Table 13: OSM2nace classification

OSM2NACE		
Class	Attribute	Value
C	Building	'industrial'
G	Shop	'copyshop', 'beverages', 'lighting', 'doors;glaziery', 'paint', 'pralines', 'sports', 'tattoo', 'car_repair', 'tea', 'mall', 'erotic', 'electrical', 'musical_instrument', 'video_games', 'outdoor', 'grocery', 'bakery', 'bed', 'perfumery', 'general', 'bathroom_furnishing', 'krantenwinkel', 'newsagent', 'mobile_phone', 'hardware', 'craft', 'lingerie', 'wine', 'supermarket', 'boutique', 'music', 'houseware', 'trade', 'butcher', 'hearing_aids', 'wholesale', 'motorcycle', 'games', 'variety_store', 'convenience', 'chemist', 'seafood', 'cosmetics', 'kitchen', 'fashion_accessories', 'gift', 'shoes', 'cheese', 'car_parts', 'pawnbroker', 'yes', 'ticket', 'multimedia', 'books', 'rental', 'furniture', 'art', 'carpet', 'curtain', 'pet', 'toys', 'garden_centre', 'tobacco', 'doityourself', 'antiques', 'doors', 'deli', 'floors', 'photo', 'computer', 'car', 'pastry', 'clothes', 'jewelry', 'charity', 'scuba_diving', 'hifi', 'stationery', 'ship_chandler', 'pet_grooming', 'baby_goods', 'frame', 'shoemaker', 'coffee', 'interior_decoration', 'alcohol', 'optician', 'fabric', 'faschion', 'greengrocer', 'running', 'lottery', 'hairdresser', 'kiosk', 'bag', 'party', 'locksmith', 'dry_cleaning', 'bicycle', 'department_store', 'confectionery', 'chocolate', 'tailor', 'camera', 'electronics', 'second_hand', 'florist', 'tyres', 'farm', 'health_food', 'laundry', 'vacuum_cleaner', 'beauty'
	Amenity	'carwash'
	Building	'retail', 'supermarket', 'commercial'
H	Amenity	'fuel', 'post_depot', 'post_office', 'vehicle_inspection', 'bicycle_parking', 'parking'
	Building	'warehouse'
I	Tourism	'apartment', 'guest_house', 'hostel', 'hotel'
	Amenity	'bar', 'biergarten', 'cafe', 'fast_food', 'food_court', 'ice_cream', 'pub', 'restaurant'
	Building	'apartments', 'house', 'residential'
J	Shop	'telecommunication'
	Office	'telecommunication', 'it'
K	Office	'bank', 'financial_advisor', 'health_insurance' 'insurance'
	Amenity	'bank'
L	Shop	'estate_agent'
	Office	'estate_agent', 'real estate'
M	Shop	'funeral_directors'
	Office	'company', 'consulting', 'advertising_agency', 'accountant', 'lawyer', 'coworking', 'yes', 'research', 'ngo', 'architect', 'notary'
	Amenity	veterinary'
	Building	'office'
N	Shop	'travel_agency'
	Office	'employment_agency'
	Amenity	'bicycle_rental'
O	Office	'government'
	Amenity	'courthouse', 'crematorium', 'fire_station', 'police', 'prison', 'public_building', 'townhall'
	Building	'government', 'fire_station'
P	Amenity	'childcare', 'college', 'kindergarten', 'school', 'university'
	Buidling	'college', 'kindergarten', 'school', 'university'
Q	Office	'physician', 'therapist'
	Amenity	'clinic', 'community_centre', 'dentist', 'doctors', 'hospital', 'nursing_home', 'pharmacy', 'refugee_housing', 'social_facility'
	Building	'civic', 'hospital'
R	Shop	'bookmaker', 'massage', 'museum'
	Sport	'ice_skating', 'gymnastics', 'rugby , atletiek', 'yes', 'golf', 'skateboard', 'board_game', 'badminton', 'soccer', 'tennis', 'basketball', 'airsoft', 'cricket', 'bowling', 'athletics;badminton;basketball;handicapped;handball;korfball;gymnastics;volleyball;soccer', 'running', 'volleyballyoga', 'equestrian', 'fishing', 'fitness', 'fitness;yoga;exercise', 'martial_arts', 'soccer;tennis;volleyball', 'table_tennis', 'hockey;badminton;soccer;volleyball;basketball;martial_arts;beachvolleyball', 'shooting_range', 'athletics', 'korfball', 'boules', 'swimming', 'billiards', 'archery', 'bowls', 'crossfit', 'sailing', 'boxing', 'climbing', 'multi', 'soccer;athletics', 'petanque', 'climbing_wall', 'scuba_diving', 'skiing'
	Leisure	'bandstand', 'bird_hide', 'bowling_alley', 'escape_game', 'fitness_centre', 'fitness_station', 'ice_rink', 'outdoor_seating', 'park', 'pitch', 'playground', 'recreation_ground', 'sport', 'sports_centre', 'sports_hall', 'stadium', 'swimming_pool', 'swimming_pool,_sauna', 'track'
	Tourism	'gallery', 'museum', 'spa_resort', 'yes', 'zoo'
	Amenity	'arts_centre', 'brothel', 'casino', 'cinema', 'conference_centre', 'exhibition_centre', 'events_venue', 'library', 'nightclub', 'theatre', 'scout_camp'
	Building	'stadium', 'recreation_ground'
S	Office	'association'
	Amenity	'monastery', 'place_of_worship'
	Building	'chapel', 'church'
T	Office	'diplomatic'