E-Laas

Energy optimal urban Logistics As A Service

Deliverable report

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Deliverable title	Simulation model with indicators of the energy assessment of distribution systems in the relation between the logistics centre and the customer's door for conducting research. Comparative analysis of distribution systems scenarios.
Scope of this report	WUT contribution to D2.3
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1. Summary

The report constitutes part of the research activities conducted within Work Package 2 (WP2) of the E-Laas project. The principal objective of this work was to develop and apply a simulation modelling framework for the analysis of urban material flows, with particular consideration given to energy consumption, emissions, operational efficiency, and the comparative assessment of alternative freight distribution scenarios.

The report builds upon the research undertaken during the preceding stages of the project. In this context, it operationalises the logistics system research scenarios and reference cases developed in Deliverable D0.3, while drawing on the methodological assumptions formulated in Report D2.1. At the present stage of the project, Deliverable D2.3 is primarily concerned with documenting the models, analytical tools, and research procedures developed within WP2. It explains how the previously defined scenarios and assumptions were translated into specific modelling approaches and subsequently applied to the assessment of urban freight distribution systems.

The report addresses four principal areas of modelling. The first concerns the macroscopic modelling of urban freight flows, energy consumption, and emissions. This level of analysis enables the metropolitan-scale impacts of urban logistics to be assessed using a transport model, data describing the transport network and Traffic Analysis Zones (TAZs), and information on traffic composition and spatial distribution. The second area concerns the microsimulation of last-mile delivery processes. At this level, delivery operations, vehicle movements, service locations, routes, and operational activities are represented in detail, thereby enabling the calculation and assessment of relevant operational performance indicators. The third area focuses on micro-macro integration for the purpose of scaling Key Performance Indicators (KPIs). Its objective is to transfer the results obtained from detailed microsimulation experiments to a broader spatial scale by applying measures of similarity between TAZs and appropriate scaling functions. The fourth area addresses micro-macro integration for system-level modelling. This approach is based on System Dynamics (SD) and supports the analysis of feedback relationships between freight demand, infrastructure availability, recipient behaviour, delivery organisation, and energy consumption. In addition, a separate research area was distinguished to encompass supplementary studies undertaken within the project, including, inter alia, analyses of freight distribution concepts incorporating intermodal transport solutions.

Deliverable D2.3 presents a structured modelling framework, the architecture of the simulation tools, the methodological logic of the scenario-based experiments, and the relevance of the results obtained in relation to the research objectives of the E-Laas project. Detailed findings, including comprehensive numerical results, comparative analyses, validation outcomes, and extended scenario variants, are documented in the associated research outputs. In the present report, these results are referenced to the extent necessary to document the research process and demonstrate the methodological coherence of the developed approach.

The principal contribution of Deliverable D2.3 lies in the formulation of an integrated modelling framework that combines operational, urban, and system-level perspectives. The

report also provides a methodological foundation for the subsequent interpretation of results within Milestone M2, where greater emphasis will be placed on the implications of the findings for the development of Sustainable Urban Logistics Policies, the identification of implementation barriers, and the assessment of prospective development pathways for urban logistics.

2. Introduction

The E-Laas project focuses on the analysis of urban logistics systems from the perspective of energy consumption, emissions, and the organisational efficiency of distribution flows. The project is based on the premise that urban logistics should not be examined merely as a collection of individual deliveries, but rather as an integrated system of flows connecting logistics operators, infrastructure, vehicles, recipients, delivery points, and the broader conditions under which cities function. Such a perspective is particularly relevant in the context of the expansion of e-commerce, the increasing volume of business-to-consumer (B2C) deliveries, the widespread adoption of parcel lockers, fleet electrification, and the growing importance of energy efficiency in urban transport.

Within the E-Laas framework, urban logistics activities are conceptualised as flows between dispatch points, logistics centres, consolidation facilities, collection points, and final recipients. These flows generate specific operational, energy-related, and environmental impacts. Their assessment requires consideration of both the parameters of individual delivery operations and the spatial structure of the city, traffic conditions, the distribution of demand, and the availability of logistics infrastructure.

One of the principal research challenges addressed by the project concerns the measurement and comparison of energy consumption across different urban freight distribution configurations. Energy may be consumed by courier vehicles, recipients' vehicles, fixed infrastructure, equipment supporting delivery operations, and other components of the logistics system. Consequently, energy assessment cannot be limited to comparisons of route length or fleet size. It must also account for the organisation of delivery processes, the structure of distribution channels, the degree of shipment consolidation, vehicle types, the contribution of recipient travel, and infrastructure-related parameters.

A key feature of the project is the multilevel character of the analysis. At the operational level, the research examines last-mile processes, including vehicle routes, service times, shipment volumes, vehicle capacities, and delivery execution parameters. At the urban level, the analysis addresses the spatial distribution of flows, transport network loads, emissions, and energy consumption across different parts of the study area. At the system level, the research investigates the relationships between demand, infrastructure, recipient behaviour, delivery technologies, and their influence on overall energy demand.

Conducting research within this framework requires the application of multiple modelling methods. Macroscopic modelling makes it possible to capture the scale and spatial differentiation of logistics-related phenomena within a city or metropolitan area. Microsimulation enables the detailed analysis of delivery processes and the generation of operational KPIs. KPI scaling methods allow results obtained for selected reference areas to be transferred to areas exhibiting similar characteristics, thereby increasing the scalability of the approach. SD, in turn, supports the analysis of feedback loops, time delays, and accumulation effects, which are characteristic of logistics systems evolving over time.

Report D2.3 documents the stage at which scenario assumptions and input data were translated into models, analytical tools, and research procedures. Earlier project reports provided the basis for this stage by defining logistics scenarios, characterising the reference cases, formulating assumptions for survey-based and simulation research, and specifying the principal data requirements. D2.3 demonstrates how these elements were subsequently used to develop a research framework for the energy assessment of urban freight distribution systems.

The report does not aim to present the complete set of detailed experimental results, but rather to systematise and document the modelling approach that was developed. Detailed findings are documented in the associated research outputs listed in the report. In D2.3, these results are presented in a synthesised form in order to demonstrate the scope of the work undertaken, the types of results obtained, and their relevance to subsequent analyses within the project.

3. Purpose and scope of the report

The objective of D2.3 is to document the development and application of simulation models and energy assessment indicators for urban freight distribution systems within WP2 of the E-Laas project. The report systematises the outcomes of research conducted across several interrelated methodological streams: macroscopic modelling of urban freight flows, microsimulation of last-mile delivery processes, micro-to-macro scaling of KPIs, and the integration of modelling results for system-level analysis.

The report is primarily documentary in nature. Its principal purpose is to present the models and tools that were developed or applied, their respective functions within WP2, the data and assumptions on which they were based, the types of experiments conducted, and the manner in which the resulting findings contribute to the broader methodological framework of the project. Research results are presented only to the extent necessary to document the work undertaken and to demonstrate the role and relevance of the individual modelling approaches, including the micro-, macro-, and integrated micro-macro levels.

The report describes the function of each model within the research task, the general methodological logic of the scenario-based experiments, the types of results obtained, and their relationship to the corresponding scientific publications. Particular emphasis is also placed on demonstrating the complementary nature of the different modelling levels. Accordingly, the scope of the report encompasses:

- documentation of the models, tools, and research procedures developed or applied within WP2;
- description of the functions performed by these models in the assessment of urban freight distribution systems;
- presentation of the general logic underlying the scenario-based experiments;

- a synthesised overview of the types of results obtained;
- identification of the relationships between the modelling results and the research outputs;
- provision of the methodological and analytical basis for achieving Milestone M2.

The report focuses on selected representative flows and research problems in urban logistics that enable the applicability of an energy-demand-based assessment approach to be examined at different levels of spatial and operational detail. The adopted structure reflects the research objectives of the E-Laas project, in which particular importance is attached to developing a scalable and transferable methodological approach rather than constructing a comprehensive implementation-oriented operational model covering all market segments and potential applications.

The interpretation of the results from the perspective of urban policy, including their implications for Sustainable Urban Logistics Policies, will be further developed at the milestone level, particularly within Milestone M2. Deliverable D2.3 provides the modelling and analytical foundation for this subsequent interpretation.

4. Research approach

The project adopted a sequential research logic, progressing from the identification of scenarios and reference cases, through the specification of data requirements and research assumptions, to model development, experimental implementation, and the synthetic assessment of results. Within this framework, Deliverable D2.3 documents the transition from the underlying research assumptions to the practical application of modelling tools. The report demonstrates how selected urban logistics scenarios were translated into macroscopic models, microsimulation models, KPI scaling procedures, and a SD approach.

The modelling activities were preceded by the identification and systematisation of scenarios for urban logistics systems. Deliverable D0.2 established a framework for scenario description, defined their principal components, and specified how relationships between actors, flows, technologies, and system operating conditions should be represented. Subsequently, Deliverable D0.3 further elaborated these scenarios and linked them to specific reference cases, particularly the Upper Silesian-Zagłębie Metropolis (GZM), which constituted one of the principal case-study areas investigated by the WUT research team.

Deliverable D2.1 served as an intermediate stage between scenario development and the modelling phase. It defined the assumptions underlying the survey-based and simulation studies, identified potential data sources, and specified the information required on freight flows, users, logistics operators, infrastructure, and logistics process parameters. D2.1 also systematised the conceptualisation of model input data, including spatial, transport-related, survey-based, and operational datasets.

Deliverable D2.2 provided complementary knowledge concerning the needs, preferences, and behaviour of urban logistics stakeholders. This information is particularly relevant in cases where modelling outcomes depend on decisions made by end users. Such decisions include the choice of delivery channel, the use of parcel lockers, the acceptable walking distance to collection points, the share of journeys undertaken by car, trip-chaining behaviour, and expectations regarding service quality.

Deliverable D2.3 incorporates these elements into the simulation modelling framework. The scenarios developed in D0.3 and the assumptions formulated in D2.1 were translated into four principal modelling streams: macroscopic modelling, microsimulation of last-mile delivery processes, KPI scaling, and system-level modelling. The outcomes documented in D2.3 subsequently provide the basis for Milestone M2, in which the emphasis shifts from the documentation of models towards the interpretation of results in the context of Sustainable Urban Logistics Policies, implementation barriers, and potential pathways for the development of urban logistics. The position of D2.3 within the overall E-Laas research procedure is presented in Table 1, while the corresponding workflow is illustrated in Fig. 1.

The adopted workflow ensures consistency between the objectives of the E-Laas project and the scenarios, data, models, and resulting implications. Consequently, two distinct levels of reporting were established. Deliverable D2.3 documents the development and application of the modelling tools, whereas Milestone M2 focuses on interpreting the results from the perspective of urban policy and identifying potential measures to support energy-efficient urban logistics.

Table 1. Position of Deliverable D2.3 within the E-Laas workflow

E-Laas Deliverable	Primary function within the project	Relevance to D2.3
D0.2	Framework for the description of logistics scenarios	Systematisation of the approach used to define scenarios and their constituent elements
D0.3	Identification of scenarios and reference cases	Selection of scenarios and study areas suitable for modelling applications
D2.1	Assumptions for survey-based and simulation research	Specification of input data, model parameters, and the methodological logic of the research
D2.2	User needs, preferences, and behaviour	Incorporation of behavioural components into the modelling framework
D2.3	Models, KPIs, experiments, and integration of results	Documentation of the tools and modelling approaches developed within the project
M2	Interpretation of results in the context of Sustainable Urban Logistics Policies	Application of modelling results to policy assessment and the formulation of recommendations

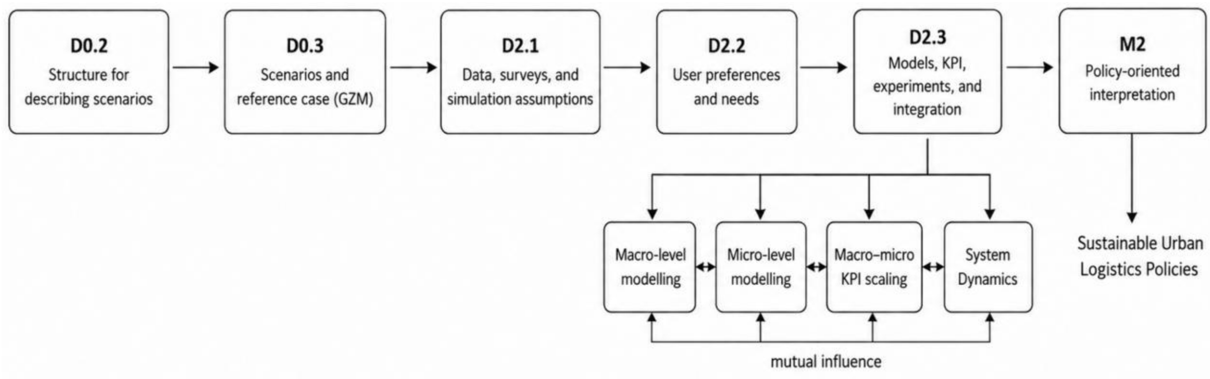

Fig. 1. Research workflow from scenarios to simulation models and policy-oriented interpretation

The modelling activities undertaken within WP2 focused on selected representative flows and research problems in urban logistics. The adopted approach was intended primarily to assess the applicability of energy-based evaluation at different levels of analytical detail (operational, spatial, and system-wide) with reference to the most representative and relevant delivery configurations in contemporary urban logistics.

In practical terms, the research concentrated on flows of particular importance to present-day urban logistics, including B2C courier deliveries, parcel lockers, collection points, last-mile delivery operations, selected vehicle configurations, and the assessment of energy- and emission-related impacts at the urban and metropolitan scales. This thematic focus made it possible to link the project scenarios with current developments in urban logistics, such as the growth of e-commerce, the expansion of out-of-home delivery channels, fleet electrification, the need to reduce emissions and the energy intensity of urban transport, and the application of intermodal solutions.

Four principal research streams were distinguished within WP2, as presented in Table 2. Their definition resulted from the analysis of modelling approaches capable of supporting a comprehensive assessment of urban logistics systems. These streams were additionally complemented by conceptual studies concerning logistics services for urban agglomerations, including, for example, solutions based on intermodal transport technologies.

Table 2. Modelling levels documented in Deliverable D2.3

Modelling level	Primary function
Macroscopic modelling	Assessment of freight flows, energy consumption, and emissions at the urban or metropolitan scale
Microscopic modelling	Detailed representation of last-mile delivery processes
Micro-macro integration for scaling	Extrapolation of microsimulation results to a broader spatial scale
System Dynamics	Analysis of dynamic relationships and feedback mechanisms

The adopted modelling levels are not independent of one another. The macroscopic model provides information on the spatial structure, transport network, TAZs, traffic conditions, and the potential spatial distribution of impacts. Microsimulation generates detailed KPI values for last-mile delivery processes. KPI scaling enables these two levels to be integrated while reducing the number of detailed simulation experiments required. SD, in turn, supports the analysis of mechanisms that evolve over time, such as increasing demand, infrastructure congestion, changes in recipient behaviour, and the effects of fleet electrification.

Accordingly, Deliverable D2.3 presents a coherent set of modelling activities in which each analytical level addresses a different type of research question. The macroscopic model addresses questions concerning the scale and spatial distribution of impacts. The microscopic model examines the detailed course and operational efficiency of delivery processes. KPI scaling addresses the issue of how microsimulation results can be extrapolated to larger spatial areas. SD investigates how changes in demand, infrastructure, and user behaviour may affect the functioning of the overall system.

In this way, D2.3 provides a basis for the further synthesis of results in the subsequent sections of the report and for their interpretation within Milestone M2. Chapters 5-8 provide a detailed description of the individual modelling layers, whereas Chapter 9 synthesises their contribution to the implementation of WP2 and discusses the supplementary research activities conducted within the project.

5. Macro-level modelling of urban freight flows, energy use and emissions

5.1. Purpose and role of macro-level modelling

Macroscopic modelling was employed in D2.3 as the principal framework for the spatial assessment of urban freight flows, energy consumption, and pollutant emissions. The objective of this component of the research was to determine how vehicle movements associated with urban logistics affect the transport network and how the resulting impacts are distributed across the spatial structure of a city or metropolitan area. From this perspective, the analysis does not focus on an individual courier route or the detailed execution of parcel-handling activities, but rather on the aggregated effects of the delivery system on the road network, TAZs, and the urban environment.

The macroscopic modelling level enables conventional transport variables, such as traffic volumes, vehicle-kilometres travelled, travel speeds, and fleet composition, to be translated into indicators of direct relevance to the E-Laas project. These include energy consumption, pollutant emissions, the external costs of emissions, and the spatial concentration of transport-related impacts. This level of analysis is particularly useful for assessing system-wide changes, such as increasing delivery demand, seasonal growth in freight transport activity, changes in fleet composition, the electrification of delivery vehicles, and the expansion of parcel collection infrastructure.

The research conducted within WP2 applied a macroscopic transport model of the Upper Silesian-Zagłębie Metropolis, developed in the PTV Visum environment and extended to incorporate the analysis of urban freight traffic. The model enabled transport flows to be linked with estimates of emissions and energy consumption based on the COPERT and HBEFA methodologies and modelling frameworks. The transport model was not included in the project dataset because it is managed by the GZM Metropolis. Access may be granted upon individual request.

From the perspective of D2.3, the macroscopic level constitutes the strategic analytical layer. It enables the identification of areas characterised by the highest energy-related and emission-related burdens, the road classes of greatest relevance to freight traffic, and the zones requiring more detailed investigation at the microscopic or system level.

5.2. Research method and data structure

The adopted research pathway integrates the transport model with an environmental assessment module (Fig. 2). The starting point is a transport network model comprising TAZs, origin-destination matrices, vehicle fleet composition, and a traffic assignment procedure. The traffic assignment results include link-level traffic volumes, vehicle-kilometres travelled, capacity utilisation, average travel speeds, and traffic loads across individual road classes. The principal stages of the research procedure are presented in Table 3.

Table 3. General procedure for the macroscopic assessment of energy consumption and emissions in urban logistics

Procedure stage	Scope	Input data	Output
Study area characterisation	Delineation of the study area and TAZs	Study area boundaries, road network, spatial data	Spatial structure of the model
Transport network representation	Definition of road classes, link lengths, capacities, and speeds	PTV Visum model / GIS data	Transport supply model
Representation of freight traffic	Identification of light commercial and heavy goods vehicles	Origin-destination matrices, traffic counts, fleet composition	Freight transport component of the model
Traffic assignment	Assignment of traffic flows to network links	Origin-destination matrices, impedance functions, link capacities	Traffic volumes, travel speeds, and Vehicle Kilometres Travelled (VKT)
Energy and emission calculations	Integration of traffic assignment results with the emission model	VKT, travel speed, vehicle category, propulsion technology	Energy consumption, emissions, and external costs
Spatial aggregation	Analysis of results at the level of network links, road classes, and TAZs	Link-level results	Maps, tables, and spatial KPIs
Scenario analysis	Comparison of alternative demand and fleet configurations	Scenario assumptions	Differences in KPI values between scenarios

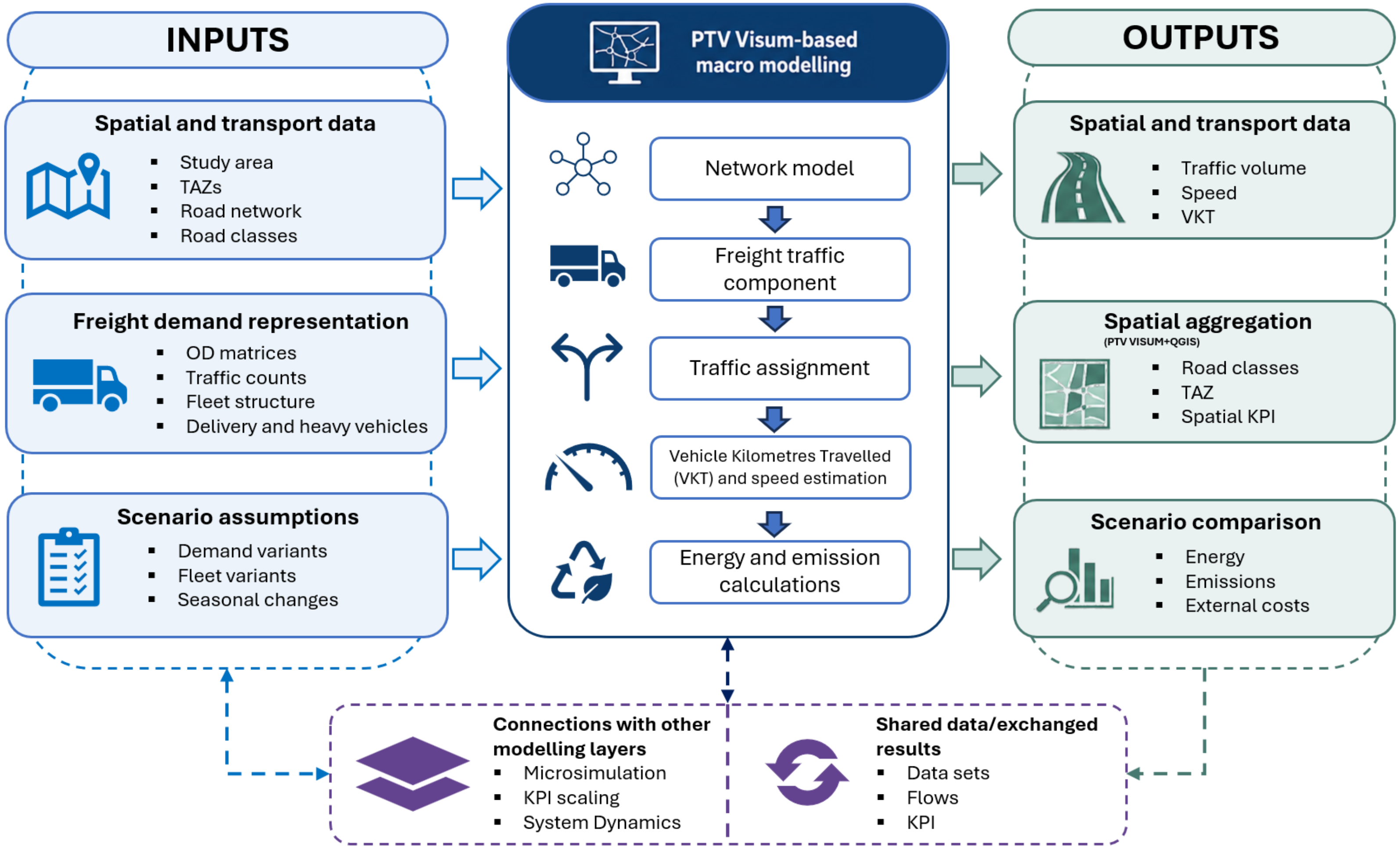

Fig. 2. General framework for macro-level assessment of urban freight energy use and emissions

On this basis, energy consumption and emission indicators are calculated. Vehicle activity is combined with energy consumption and emission factors that vary according to vehicle category, propulsion technology, travel speed, and traffic conditions. The results may be analysed at the level of individual network links, road classes, TAZs, or the entire study area. This structure enables both an assessment of the overall impacts of freight transport and the identification of locations where environmental impacts are particularly pronounced.

The GZM was adopted as the principal reference case. GZM is a polycentric metropolitan area comprising 41 municipalities, covering approximately 2,500 km² and inhabited by more than 2.1 million residents. It is characterised by a complex settlement structure, a high degree of urbanisation, substantial industrial and service-sector activity, and an extensive transport network. These characteristics make it a suitable case study for analysing urban and metropolitan freight flows. A general overview of the study area is provided in Table 4.

Table 4. Characteristics of the GZM macroscopic reference case

Element	Characteristics	Relevance to D2.3
Study area	Upper Silesian-Zagłębie Metropolis	Reference Case RC1
Scale	41 municipalities, approximately 2 500 km²	Metropolitan-scale analysis
Population	More than 2,1 million inhabitants	High potential urban freight demand
Analytical tools	PTV Visum, supported by QGIS	Macroscopic transport network and traffic model
Total vehicle-kilometres travelled	2 629 777 veh-km	Reference value for overall traffic assessment
Freight vehicle-kilometres travelled	419 675 veh-km	Approximately 16% of total vehicle-kilometres travelled
Road classes	A, S, GP, G, Z, L, and service roads	Analysis of the functional structure of the road network
Environmental assessment	COPERT and HBEFA models	Energy consumption, emissions, and external emission costs

The GZM model comprised a road network divided into functional classes, including motorways, expressways, principal roads designed for accelerated traffic, main roads, collector roads, local roads, and service roads. At the network-link level, data were available on link length, link type, capacity, traffic volume, vehicle composition, and vehicle-kilometres travelled. In the baseline scenario, total vehicle activity within the model amounted to 2,629,777 vehicle-kilometres, of which 419,675 vehicle-kilometres, corresponding to approximately 16%, were attributed to freight vehicles. These figures indicate that freight transport does not quantitatively dominate overall road traffic; nevertheless, it constitutes a significant component of network loading and should therefore be distinguished explicitly in energy and emission analyses.

The representation of freight traffic requires an adaptation of the conventional four-step transport modelling procedure. In passenger transport, trip generation is determined primarily by the spatial distribution of population, employment, educational facilities, services, and socio-economic activities. Freight transport, by contrast, is influenced by a different set of generators and attractors, including warehouses, wholesale facilities, manufacturing plants, retail establishments, restaurants, service facilities, logistics centres, parcel lockers, pick-up and drop-off (PUDO) points, and areas characterised by high levels of consumer demand.

For the i-th TAZ, the freight traffic generation and attraction potential can be expressed in general form as follows (Eq. 1 and Eq. 2):

$$FTP_i = f(X_i^{prod}) \tag{1}$$

$$FTA_i = f(X_i^{attr}) \tag{2}$$

where:
FTP_i - freight trip production in the i-th TAZ,
FTA_i - freight trip attraction in the i-th TAZ,
X_i^{prod} - TAZ-specific characteristics influencing freight trip generation,
X_i^{attr} - TAZ-specific characteristics influencing freight trip attraction.

The matrix of freight flows between TAZs can be expressed as follows (Eq. 3):

$$Q_{ij}^F = g(FTP_i, FTA_j, c_{ij}) \tag{3}$$

where:
Q_{ij}^F - the number of freight trips between i-th and j-th TAZs,
c_{ij} - the impedance of travel between the TAZs, expressed, for example, in terms of distance, travel time, or cost.

The precise estimation of these values is constrained by the limited availability of data on urban freight flows. Data held by logistics operators are fragmented and are frequently subject to commercial confidentiality, while administrative datasets do not always permit the actual structure of delivery activities to be reconstructed. Consequently, the research conducted within WP2 adopted an integrated approach combining macroscopic model data, spatial data, information on urban land-use functions, traffic counts, survey data, and scenario assumptions.

5.3. Energy, emission and external-cost assessment

The basic computational unit in the macroscopic model is a transport network link. For the l-th link, information was specified on its length, traffic volume, vehicle composition, average travel speed, and road class. These variables provide the basis for calculating vehicle activity and the associated energy consumption and emissions.

Energy consumption on the l-th link under s-th scenario can be expressed as shown in Eq. 4. Analogously, emissions of the p-th pollutant can be calculated using Eq. 5.

$$E_l^s = \sum_{v \in V} q_{l,v}^s \cdot L_l \cdot e_v(\bar{v}_l^s) \tag{4}$$

$$M_{l,p}^s = \sum_{v \in V} q_{l,v}^s \cdot L_l \cdot EF_{v,p}(\bar{v}_l^s) \tag{5}$$

where:
E_l^s - energy consumption on the l-th link in the s-th scenario,
$q_{l,v}^s$ - number of vehicles of the v-th class on the l-th link in the s-th scenario,
L_l - length of the l-th link,
$e_v(\bar{v}_l^s)$ - unit energy consumption of a vehicle of the v-th class, dependent on the average speed on the l-th link,
$\bar{v}_l^s$ - average speed on the l-th link in the s-th scenario,
$M_{l,p}^s$ - mass of the p-th pollutant emitted on the l-th link in the s-th scenario,
$EF_{v,p}$ - emission factor for the p-th pollutant and the v-th class of a vehicle.

In the GZM case study, the calculations were performed using COPERT and the HBEFA model. The analysis accounted for pollutant emissions and energy consumption associated with both internal combustion engine vehicles and electric vehicles. Fuel consumption was converted into energy units, thereby enabling the impacts of different fleet compositions to be compared. Emission costs were calculated using the relationship presented in Eq. 6:

$$C_l^s = \sum_{p \in P} \frac{M_{l,p}^s}{10^6} \cdot c_p \tag{6}$$

where:
C_l^s - emission cost on the l-th link in the s-th scenario,
$M_{l,p}^s$ - mass of the the p-th pollutant emitted on the l-th link in the s-th scenario, expressed in grams,
c_p - unit cost of emissions of the p-th pollutant, expressed in EUR/t.

Link-level calculations enable the identification of locations characterised by the highest environmental burdens. This has practical significance because total emissions calculated for the city as a whole do not indicate where infrastructure, regulatory, or organisational measures should be implemented. Only spatially disaggregated analysis makes it possible to relate emissions to road class, land-use function, traffic intensity, and the share of delivery vehicles.

The results obtained at the network-link level may subsequently be aggregated by road class and TAZ. Aggregation by road class enables an assessment of the elements of the transport infrastructure on which vehicle activity, energy consumption, and emissions are concentrated. Aggregation by TAZ makes it possible to relate the results to the spatial function of a given area, such as residential, commercial, industrial, warehousing, or logistics-related use.

Energy consumption and emissions of the p-th pollutant in the z-th TAZ can be expressed as shown in Eq. 7 and Eq. 8:

$$E_z^s = \sum_{l \in L_z} E_l^s \tag{7}$$

$$M_{z,p}^s = \sum_{l \in L_z} M_{l,p}^s \tag{8}$$

where:
L_z - the set of network links assigned to the z-th TAZ,
E_z^s - energy consumption in the z-th TAZ in the s-th scenario,

$M_{z,p}^{s}$ - emissions of the p-th pollutant in the z-th TAZ in the s-th scenario.

For spatial comparisons, density-based indicators of energy consumption and emission costs are also useful (Eq. 9 and Eq. 10):

$$ED_z^s = \frac{E_z^S}{A_z} \tag{9}$$

$$CD_z^s = \frac{C_z^S}{A_z} \tag{10}$$

where:
ED_z^s - energy consumption density in the z-th TAZ in the s-th scenario,
CD_z^s - emission cost density in the z-th TAZ in the s-th scenario,
A_z - area of the z-th TAZ.
The GZM study also used a transit index (Eq. 11) that helps to interpret whether the environmental burden assigned to a TAZ is mainly related to local activity or to vehicles passing through the zone. Higher values indicate TAZs with a stronger transit or corridor role, where energy use and emissions may be high even if the local transport-generating potential is limited.

$$TR_z = \frac{TK_z}{I_z} \tag{11}$$

where:
TR_z - transit index of the z-th TAZ,
TK_z - total vehicle-kilometres travelled on the network links assigned to the z-th TAZ,
I_z - intensity of the transport-related functions and transport-generating potential of the z-th TAZ.

The results obtained for GZM confirmed the spatial heterogeneity of transport-related impacts. The highest levels of energy consumption and emissions associated with total traffic were concentrated along the principal transport corridors. In the case of freight traffic, significant impacts were observed not only on higher-class roads, but also on network links serving areas characterised by intensive logistics and economic activity. Selected results aggregated by road class are presented in Table 5.

Table 5. Examples of unit energy consumption values by road class in the GZM study

Road class	Unit energy consumption for total traffic	Unit energy consumption for freight traffic	Interpretation
A	Appr. 3.4 MJ/veh-km	Appr. 6.3 MJ/veh-km	High traffic volumes and high travel speeds
S	Appr. 3.2 MJ/veh-km	Appr. 6.3 MJ/veh-km	Significant shares of transit and freight traffic
GP	Appr. 2.7 MJ/veh-km	Appr. 5.6 MJ/veh-km	Relatively stable traffic conditions
G	Appr. 2.6 MJ/veh-km	Appr. 5.6 MJ/veh-km	Urban traffic of substantial system-wide importance
Z	Appr. 2.6 MJ/veh-km	Appr. 6.0 MJ/veh-km	Greater influence of stopping events and traffic variability

L	Appr. 2.6 MJ/veh-km	Appr. 5.9 MJ/veh-km	Local traffic and final-stage delivery operations
Service	Appr. 2.8 MJ/veh-km	Appr. 6.3 MJ/veh-km	Operational traffic characteristics and limited traffic fluidity

Table 5 demonstrates that road class alone does not determine the level of energy consumption. Other relevant factors include travel speed, traffic fluidity, the share of freight vehicles, and the functional characteristics of the area served. The higher values observed for freight vehicles result from their greater mass, propulsion characteristics, and higher sensitivity to traffic conditions. Importantly, road class itself appears to play a comparatively less significant role in this respect.

5.4. Macro-level scenario experiments and selected results

The scenario analysis enabled an assessment of how the transport system responds to changes in freight demand and fleet composition. The GZM case study examined a baseline scenario, a scenario involving an increase in freight traffic, and a scenario involving the electrification of delivery vehicles. The freight traffic growth scenario represents periods of increased delivery activity, such as seasonal peaks in demand or the continued expansion of e-commerce. The electrification scenario enables the effects of replacing internal combustion engine vehicles with zero-emission vehicles to be assessed in terms of local emissions and the structure of energy consumption.

A synthesised overview of the scenarios is presented in Table 6. The change in a given indicator under the s-th scenario, relative to the baseline scenario, can be expressed as shown in Eq. 12:

$$\Delta KPI^{s} = \frac{KPI^{s} - KPI^{S*}}{KPI^{S*}} \cdot 100\% \qquad (12)$$

where:
KPI^{S*} - value of the indicator in the baseline scenario,
KPI^{s} - value of the indicator in the s-th scenario under analysis.

Table 6. Scope of interpretation of the macroscopic scenarios

Scenario	Nature of change	Variable	Purpose of the analysis
S0	Representation of average traffic conditions	Traffic and fleet structure in the baseline model	Reference scenario
S1	Increase in delivery activity	Generation and attraction of freight traffic	Assessment of increases in energy consumption, emissions, and external costs
S2	Change in vehicle technology through electrification	Propulsion structure of delivery vehicles	Assessment of reductions in local emissions and changes in the energy carrier structure

The scenario results indicated that an increase in freight transport demand leads to higher energy consumption and emissions; however, the magnitude of these increases depends on road class and the spatial distribution of traffic. Fleet electrification reduces local emissions attributable to delivery vehicles, but does not eliminate energy demand. Rather, it primarily changes the energy carrier and generates additional requirements for charging infrastructure.

This finding is particularly relevant to the project, as energy provides a common basis for comparing alternative organisational and technological solutions. The scenario results, including analyses conducted at the levels of individual network links, road classes, and TAZs, are presented in publication [14]. Further methodological developments concerning the application of macroscopic transport and emission models to the assessment of freight transport impacts, as well as the validation of the COPERT and HBEFA models, are discussed in [14] and in the associated methodological study [15].

5.5. Complementary modelling components supporting macro-level assessment

The macroscopic assessment of freight traffic was complemented by detailed models that enable selected components of the urban logistics system to be interpreted more accurately. These components include, in particular, recipient mobility associated with parcel lockers, urban delivery planning, the allocation of vehicles to delivery tasks, and the energy intensity of electric delivery vehicles.

The expansion of parcel locker networks alters the distribution of vehicle activity within the last-mile delivery system. Part of the transport activity previously performed by couriers in the home-delivery (HOME) model is replaced by consolidated deliveries to collection points. At the same time, an additional component of recipient mobility emerges, which may involve walking, cycling, public transport, or private car use. From the perspective of energy consumption and emissions, car journeys are of particular relevance, especially when undertaken exclusively for the purpose of collecting a parcel.

The study of induced travel to parcel lockers used survey data and spatial data describing the distribution of population and parcel locker locations within GZM. The model accounted for the number of parcels collected by users, the proportion of parcels delivered to parcel lockers, the share of dedicated collection trips, acceptable walking time, and modal split. The results revealed substantial differences between urban and less urbanised areas. In urban areas, a large proportion of residents are located within an acceptable walking distance of a parcel locker, whereas in peripheral areas pedestrian accessibility is more limited and may result in a higher number of car journeys. The research conducted in this area is presented in publication [13].

The general expression for vehicle-kilometres travelled generated by recipients can be formulated as shown in Eq. 13:

$$VKT_{APM}^{cust} = \sum_{r \in R} N_r \cdot f_r \cdot P_{car,r} \cdot d_{r,APM} \cdot \alpha \tag{13}$$

where:
VKT_{APM}^{cust} - vehicle-kilometres travelled generated by parcel recipients,
N_r - number of residents or households in the r-th location,
f_r - parcel collection frequency in the r-th location,

$P_{car,r}$ - probability of using a car to collect a parcel in the r-th location,
$d_{r,APM}$ - distance from the r-th location to the nearest parcel locker,
α - adjustment factor accounting for the return journey, network circuity, or trip-chaining effects.

Accounting for recipient travel extends the conventional assessment of urban freight transport. A delivery system cannot be regarded as terminating at the point at which a parcel is deposited in a parcel locker if the recipient is required to undertake an additional journey to collect it. Consequently, the energy assessment of out-of-home (OOH) delivery channels should consider the combined effect of reduced courier vehicle activity, changes in the degree of shipment consolidation, and additional user mobility. This issue was also examined in the associated System Dynamics study [17], which applied SD to assess the behaviour of the urban logistics system and the energy demand associated with delivery operations.

As a further complement to the macroscopic analyses, research was conducted on delivery planning in urban areas. Publication [7] presents a multi-criteria approach incorporating cost, delivery time, and environmental exposure to pollutant emissions. Models of this type translate macroscopic findings into operational decision-making by demonstrating how delivery activities can be planned while simultaneously accounting for efficiency and environmental impacts.

Additional conceptual research investigated the use of intermodal transport from a central distribution hub (in this case, the Central Communication Port) through urban terminals to final recipients, using BDF swap bodies. The associated conceptual study indicates the potential to reduce the role of road transport in last-mile deliveries and suggests that delivery distances within a large city could potentially be reduced by several tens of percent [4].

Another component of relevance to urban logistics concerns models for the risk-aware allocation of vehicles to delivery tasks. In publication [2], a decision model was developed to minimise the probability of hazardous events occurring along vehicle routes. An ant colony optimisation algorithm was subsequently applied to identify solutions satisfying constraints related to travel time and acceptable risk levels. In the context of E-Laas, this demonstrates the potential to extend the assessment of delivery systems to include resilience, safety, and reliability criteria alongside energy consumption and emissions.

From the perspective of fleet electrification, modelling vehicle energy demand is also of considerable importance. Predictive models developed in this research area account for route-segment length, gross vehicle mass including the transported load, departure time from the depot, the number of loading and unloading points, the number of stops imposed by transport infrastructure, terrain gradient, and wind speed [3]. The regression model of electric vehicle energy consumption can be expressed as shown in Eq. 14:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \varepsilon \tag{14}$$

where:
Y - energy consumption,
x_1 - length of the route segment,

x_2 - gross vehicle mass, including the transported load,
x_3 - departure time from the depot,
x_4 - number of service points and stops,
x_5 - terrain gradient,
x_6 - wind speed.

Models capable of estimating vehicle energy demand are particularly relevant to electrification scenarios. At the macroscopic level, fleet electrification contributes to reducing local emissions, whereas vehicle-level models enable energy requirements to be estimated more precisely as a function of route conditions, vehicle mass, congestion, and the operational characteristics of delivery services.

The supplementary studies conducted within the E-Laas project make an important contribution to the analysis of urban logistics systems and to the further assessment of potential factors influencing energy consumption. Consequently, they also support the examination of issues related to the design of urban distribution systems and the formulation of urban logistics policies. An overview of the studies extending the analytical perspective is provided in Table 7.

Table 7. Supplementary studies complementing the macroscopic modelling level

Research area	Publication	Role in D2.3
Induced travel to parcel lockers	Paszkowski & Żochowska (2025) [13]	Extension of the macroscopic assessment to incorporate recipient mobility
Delivery planning incorporating environmental considerations	Lasota et al. (2024) [7]	Transition from spatial assessment to operational decision-making
Vehicle allocation and risk	Izdebski (2023) [2]	Incorporation of route-related risk, safety, and reliability
Energy consumption of electric vehicles	Izdebski & Jacyna (2025) [3]	Refinement of energy-related parameters for electrification scenarios
Assessment of macroscopic transport and emission models	Paszkowski & Szczepański (2026) [15]	Methodological development of the integration of transport and emission models
Delivery planning using intermodal transport	Jachimowski (2026) [4]	Analysis of multimodal delivery systems and their energy efficiency

5.6. Contribution to D2.3 and further integration

The macroscopic component of the research provided a methodological framework for assessing urban freight flows at the scale of the entire metropolitan area. The developed procedure enables the transport model to be integrated with the assessment of energy consumption, emissions, and external costs, followed by the spatial analysis of results at the level of network links, road classes, and TAZs.

The principal value of the macroscopic level lies in its capacity to assess both the magnitude and spatial distribution of impacts. This makes it possible to identify the elements of the road network and the urban areas associated with the highest energy- and emission-related burdens. Such an assessment is relevant both to the analysis of the existing delivery system and to the evaluation of alternative scenarios, including increased demand, vehicle electrification, the expansion of collection-point networks, and the reorganisation of delivery operations.

The results obtained at the macroscopic level provide a basis for subsequent integration with microsimulation and system-level models. Of particular relevance are data describing TAZs, network structure, traffic conditions, and the spatial distribution of vehicle-kilometres travelled. For the subsequent analysis of urban policies, particular importance is attached to the relationships between demand, fleet composition, infrastructure availability, delivery channels, recipient mobility, energy consumption, and emissions.

Accordingly, the macroscopic level serves as the strategic analytical layer within D2.3. It supports the assessment of the magnitude and spatial distribution of urban logistics impacts, identifies areas requiring more detailed investigation, and provides input data for KPI scaling and further simulation modelling.

6. Micro-level modelling of last-mile logistics processes

6.1. Purpose and role of micro-level modelling

Micro-level modelling was used in D2.3 as the operational layer of the energy and emission assessment of last mile delivery in urban distribution systems. While the macro-level model, presented in chapter 5, represents the aggregate spatial impact of last mile delivery movement on the transport network, the micro level reproduces the individual last-mile delivery processes that generate this movement. The object of analysis at this level is the single delivery operation: the assignment of shipments to vehicles, the route followed, the load carried, the energy expended and the resulting CO_2 emissions. The purpose of this part of the research was to quantify and compare the energy intensity and emissions of alternative delivery modes and organisational variants under controlled, reproducible conditions to feed macro-level models.

The micro-level assessment was implemented as a discrete-event simulation (DES) of a last-mile delivery system in FlexSim simulation environment. The simulation reproduces demand generation, vehicle dispatching, vehicle routing, service execution, clustering and per-segment energy and emission accounting, and aggregates the results into KPIs per delivery mode and per scenario. Scenarios can cover modal shift, vehicle structure changes and demand variability. This makes it possible to isolate the effect of a single factor, such as fleet composition or parcel collection channel, on energy use and emissions, while holding the remaining factors constant.

The reference area is the Polish reference case RC1, the GZM. The road network, demand points and energy conversion factors were calibrated for the central part of the conurbation (approximately 50.26 N, 19.02 E, the Katowice area) and for the Polish electricity-generation mix. Within the overall D2.3 workflow, the micro level provides the operational evidence that the scenarios identified in D0.3 can be executed as simulation experiments and produce comparable, decision-relevant indicators usable for macro-level simulation. The resulting KPIs also serve as inputs to the KPI-scaling approach (chapter 7) and to the SD energy accounting (Chapter 8).

6.2. Research method and data structure

The micro-level model was built in the FlexSim discrete-event simulation environment (v. 25.1.5), with the delivery and assessment logic implemented as custom functions. The architecture of the framework model allows it to represent any transport network described by the data sets specified in [19]. The model exported to an XML flat file is available in the dataset [20]. Simulation studies are performed iteratively using a random number generator with variable seed values. **This report briefly summarizes the research results discussed in the article [9].**

The main research procedure links a representation of demand, a road-network graph, a vehicle and conversions dictionary, parametrization tools and a route-optimisation engine, and produces a per-mission log that is subsequently aggregated into KPI. The processing chain is shown in Fig. 3.

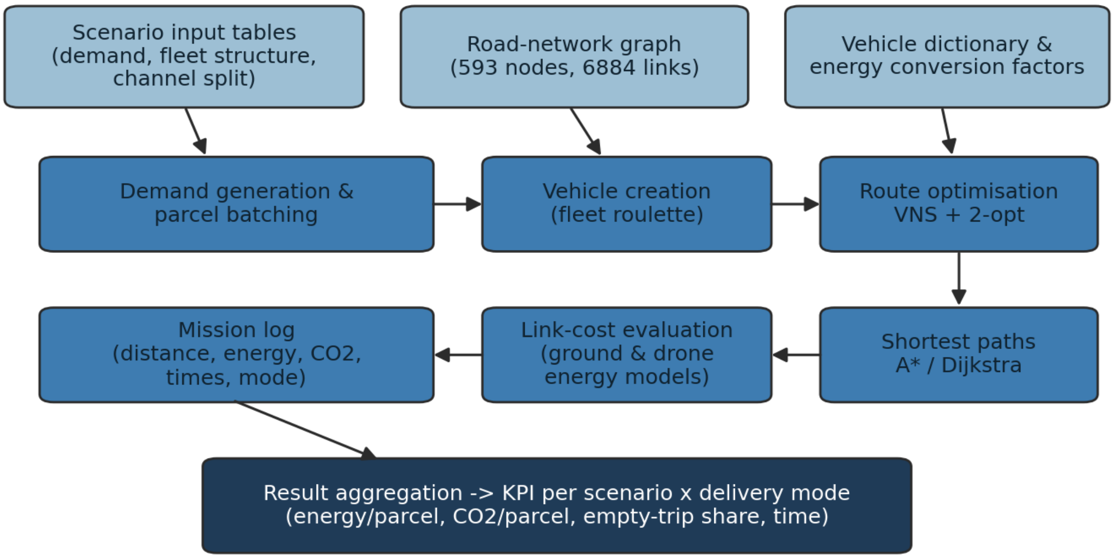

Fig. 3. Processing chain of the micro-level last-mile delivery simulation

The transport network is represented by a directed road-network graph derived from a VISUM-type network for the reference area. The reference-case graph comprises 593 nodes and 6884 links – each link carries its length, free-flow speed and the set of permitted transport modes, and each node stores its geometric coordinates. Demand and service points are attached to the nearest local network node. The reference-case point layer includes 410 restaurants, 1897 residential buildings, 51 office buildings and 105 parcel lockers, which act as origins and destinations depending on the scenario. The performance design of the simulation model allows for handling practical cases with a scale 2-3 times larger than the reference case.

Vehicle routing is formulated as a capacitated multiple travelling-salesman problem with time windows. For a single vehicle, a route over a set of terminal nodes (depot and delivery addresses) is optimised subject to capacity constraints (volume, mass or piece count) and time-window constraints, the multiple-route character follows from the many vehicles and missions executed in the simulation. The cost of an ordering of terminals is evaluated on a matrix of shortest-path costs between terminals, as given in Eq. 15.

$$C(\pi) = \sum_{p=1}^{m-1} D_{\pi_p,\pi_{p+1}} + \mathrm{backToDepot} \cdot D_{\pi_m,\pi_1} \tag{15}$$

where:

$\pi = (\pi_1, \pi_2, \dots, \pi_m)$ - sequence of terminals visiting, π_1 is a depot,
$D_{\pi_p,\pi_{p+1}}$ - minimum cost of travel between subsequent terminals,
m - number of terminals on the route,
$\mathrm{backToDepot}$ - route closing binary parameter.
D_{π_m,π_1} - the cost of returning from the last terminal to the base.

The ordering is optimised by a Variable Neighbourhood Search (VNS) combined with 2-opt local search: at each iteration the current order is perturbed by k successive 2-opt moves and then improved to a local optimum, the neighbourhood size k is reset on improvement and increased otherwise, and the search terminates after a fixed number of non-improving iterations. The shortest-path costs for a node matrix $\boldsymbol{D}[i,j]$ and the corresponding paths are computed on the network graph by an A* search with an admissible Euclidean heuristic, with a Dijkstra option for verification. Unreachable terminal pairs are assigned a prohibitive cost rather than rejected, so that every demand configuration yields a feasible, penalised solution.

For network areas in which consecutive delivery addresses without direct road-network connectivity are mapped to a selected road-network node, a local neighbourhood search is conducted using two-dimensional Euclidean distances and resource-type-specific movement characteristics within the corresponding residential zone. The set of delivery points assigned to a single courier is formed using a constrained anchor-based greedy procedure rather than a global clustering method.

Within the earliest pending time-window group (W^*), the supplier with the largest number of pending delivery points is selected. The cluster anchor is then defined as the delivery point located farthest from the selected supplier, as specified in Equation (16). The remaining delivery points are ordered by ascending Euclidean distance from the anchor and added to batch B, provided that the volume-capacity, piece-count, and time-window constraints defined in Eq. 17 are satisfied. The internal visiting order of the delivery points included in B is subsequently determined by the route optimiser using the objective function defined in Eq. 15. Thus, the batching procedure determines cluster membership only and does not specify the delivery sequence.

$$c = \arg\max_{q} \parallel x_q - x_{s^*} \parallel_2 \tag{16}$$

$$B = \left\{ q \text{ ordered by ascending } \parallel x_q - x_c \parallel_2 : \sum_{q \in B} v_q \le V_{\max},\ \mid B \mid \le N_{\max} = 20,\ w_q \in W^* \right\} \tag{17}$$

Demand is generated per scenario from dedicated input tables. Ready-meal demand is generated as a Poisson process per restaurant, modulated by an hourly factor with pronounced lunch and dinner peaks. Boxed-meal demand is defined as the expected number of deliveries per day per residential or office point, served within fixed delivery time windows. Parcel demand is defined per building as a common parcel volume that is split between delivery channels (home delivery and parcel locker with different picking options) according to a channel-split table (this single demand is never duplicated across channels). Vehicle composition is drawn for each mission from a scenario-specific fleet structure in which the shares of the individual vehicle types sum to one.

The set of delivery modes distinguished in the model corresponds to the segments identified in D0.3 and is encoded by the mode index LMD_mode (LMD = last mile delivery):

1. Ready-meal delivery from restaurants
2. Direct courier delivery to the home
3. Delivery from the hub to parcel lockers
4. Parcel collection from a locker by the client
5. Drone delivery from a parcel locker
6. Direct drone delivery
7. Boxed-meal delivery (catering).

Modes 5 and 6 use a dedicated drone energy model, the remaining modes use the ground-vehicle model (Section 6.3). Modes 3 and 4, as well as 3 and 5, when considered sequential, create a whole delivery path for parcels from hub to clients' locations.

The scenarios identified in D0.3 for the reference case RC1 were translated into simulation experiments in three process families:

- ready-made food delivery,
- boxed-meal delivery,
- parcel delivery.

The parcel delivery scenarios were implemented as a single parcel demand distributed between home delivery, parcel locker delivery, self-pick-up and drone-based variants. This structure corresponds to BS 1.3 and AS 1.3.1–AS 1.3.10 in D0.3. Pharmaceutical delivery (BS/AS 1.4) and B2B urban freight deliveries (BS/AS 1.5) were retained as directions for future research and were not implemented as full micro-level simulation experiments in D2.3. The mapping between the D0.3 scenarios and the executed simulation runs is summarised in Table 8.

Table 8. Mapping of D0.3 scenarios to executed micro-level simulation runs

D0.3 reference	Scenario (process family)	Scenarios' IDs	Active LMD modes	Variable modified vs. base
BS 1.1	Ready-made food delivery	FOOD_BS_1_1	1	*Reference case*, base fleet structure, base demand
AS 1.1.1	Ready-made food delivery	FOOD_AS_1_1_1	1	Modal split and moderate low-emission fleet structure
AS 1.1.2	Ready-made food delivery	FOOD_AS_1_1_2	1	Demand ×1,25 and low-emission fleet structure
AS 1.1.3	Ready-made food delivery	FOOD_AS_1_1_3	1	Demand ×1,25 and zero-emission fleet structure

D0.3 reference	Scenario (process family)	Scenarios' IDs	Active LMD modes	Variable modified vs. base
BS 1.2	Boxed-meal delivery	FB_BS_1_2	7	*Reference case*, base fleet structure, base demand
AS 1.2.1	Boxed-meal delivery	FB_AS_1_2_1	7	Base demand and moderate low-emission fleet structure
AS 1.2.2	Boxed-meal delivery	FB_AS_1_2_2	7	Demand ×1,25 and low-emission fleet structure
AS 1.2.3	Boxed-meal delivery	FB_AS_1_2_3	7	Demand ×1,25 and zero-emission fleet structure
BS 1.3	Parcel delivery (combined)	PKG_BS	2,3,4	*Reference case*, base demand, direct home delivery 35%, delivery through parcel lockers 65%, base fleet structure and base structure of client's vehicles
AS 1.3.1	Parcel delivery (combined)	PKG_AS_1_3_1	2,3,4	Base demand, direct home delivery 35%, delivery through parcel lockers 65%, moderate low-emission fleet structure, moderate low-emission clients' vehicles structure
AS 1.3.2	Parcel delivery (combined)	PKG_AS_1_3_2	2,3,4	Base demand, direct home delivery 35%, delivery through parcel lockers 65%, low-emission fleet structure, low-emission clients' vehicles structure
AS 1.3.3	Parcel delivery (combined)	PKG_AS_1_3_3	2,3,4	Base demand, direct home delivery 35%, delivery through parcel lockers 65%, zero-emission fleet structure, low-emission clients' vehicles structure
AS 1.3.4	Parcel delivery (drone from locker)	PKG_AS_1_3_4	2,3,5	Base demand, direct home delivery 35%, delivery through parcel lockers 65%, base fleet structure, drone delivery from lockers to clients
AS 1.3.5	Parcel delivery (channel split)	PKG_AS_1_3_5	2,3,4	Base demand, direct home delivery 0%, delivery through parcel lockers 100%, base fleet structure, base clients' vehicles structure
AS 1.3.6	Parcel delivery (channel split)	PKG_AS_1_3_6	2,3,4	Base demand, direct home delivery 25%, delivery through parcel lockers 75%, base fleet structure, base clients' vehicles structure
AS 1.3.7	Parcel delivery (channel split)	PKG_AS_1_3_7	2,3,4	Base demand, direct home delivery 50%, delivery through parcel lockers 50%, base fleet structure, base clients' vehicles structure
AS 1.3.8	Parcel delivery (channel split)	PKG_AS_1_3_8	2,3,4	Base demand, direct home delivery 75%, delivery through parcel lockers 25%, base fleet structure, base clients' vehicles structure
AS 1.3.9	Parcel delivery (channel split)	PKG_AS_1_3_9	2,3,4	Base demand, direct home delivery 100%, delivery through parcel lockers 0%, base fleet structure, base clients' vehicles structure
AS 1.3.10	Parcel delivery (direct drone)	PKG_AS_1_3_10	6	Base demand, direct home delivery 100% by drones

The energy parameters of the transport modes were taken from a common vehicle dictionary of 20 vehicle types. Selected parameters used by the energy model are listed in Table 9. Ground vehicles are described by empty-load and full-load consumption rates per 100 km, drones are described additionally by their take-off mass, propulsion efficiency and the power ratios used in the momentum-theory model (Section 6.3).

Table 9. Selected vehicle types and energy-model parameters (excerpt from the vehicle dictionary)

Vehicle type	Power system	Max speed [km/h]	Capacity V [m³]	Capacity M [kg]	Capacity P [pcs]	Fuel capacity [fuel unit]	Energy capacity [kWh]	Fuel cons. empty [fuel unit/100km]	Fuel cons. loaded [fuel unit/100km]	Energy cons. empty [kWh/100km]	Energy cons. loaded [kWh/100km]	Climb speed empty [km/h]	Climb speed loaded [km/h]	Fuel unit
pedestrian	No power	4,5	0,1	15	5	0	0	0	0	0	0	0	0	-
van_diesel	Diesel	90	6	1000	100	60	0	8	11	0	0	0	0	l
van_gasoline	Gasoline	90	6	1000	100	60	0	8	9	0	0	0	0	l
van_electric	Electric	90	6	1000	100	0	75	0	0	25	30	0	0	-
truck_6pallet_diesel	Diesel	80	14,5	1500	300	200	0	10	15	0	0	0	0	l
truck_6pallet_electric	Electric	80	14,5	1500	300	0	300	0	0	80	100	0	0	-
truck_6pallet_H	Hydrogen	80	14,5	1500	300	40	0	8	10	0	0	0	0	kg
truck_6pallet_CNG	CNG	80	14,5	1500	300	80	0	22	26	0	0	0	0	kg
car_diesel	Diesel	130	0,5	300	20	45	0	7	9	0	0	0	0	l
car_gasoline	Gasoline	130	0,5	300	20	45	0	7	8	0	0	0	0	l
car_electric	Electric	130	0,5	300	20	0	60	0	0	16	20	0	0	-
car_LPG	LPG	130	0,5	300	20	40	0	9	10	0	0	0	0	l
car_H	Hydrogen	130	0,5	300	20	6	0	1	1,2	0	0	0	0	kg
scooter_gasoline	Gasoline	50	0,08	25	5	6	0	3	3,5	0	0	0	0	l
scooter_electric	Electric	45	0,08	25	5	0	3	0	0	4	5	0	0	-
bicycle	No power	25	0,06	15	3	0	0	0	0	0	0	0	0	-
cargo_drone_small	Electric	60	0,03	5	3	0	2	0	0	1,5	2	36	28,8	-
cargo_drone_large	Electric	60	0,15	15	3	0	15	0	0	6	8	28,8	21,6	-
e_scooter_kick	Electric	25	0,03	10	3	0	0,5	0	0	1,2	1,5	0	0	-
bicycle_electric	Electric	25	0,06	15	3	0	0,5	0	0	0,8	1	0	0	-

The CO_2 factor for electricity (0.618 kg CO_2/kWh) reflects the Polish generation mix [10]. The factors for liquid and gaseous fuels follow standard emission and energy-equivalent values. These factors provide the common energy and CO_2 denominator that allows organisationally and technologically different delivery options to be compared. Table 10 presents the universal energy conversion factors used in model.

Table 10. Universal energy conversion factors

From	To	Value
No fuel	kg of CO_2	0
1 kWh	kg of CO_2	0,618
1 l of gasoline	kg of CO_2	2,31
1 l of diesel	kg of CO_2	2,68
1 kg of H_2	kg of CO_2	0
1 kg of CNG	kg of CO_2	2,70059
1 l of LPG	kg of CO_2	1,66
1 l of gasoline	kWh	8,88
1 l of diesel	kWh	10
1 kg of H_2	kWh	33,33
1 kg of CNG	kWh	12,3
1 l of LPG	kWh	6,7
1 kWh	MJ	3,6
1 l of gasoline	MJ	32,1
1 l of diesel	MJ	35,9
1 kg of H_2	MJ	120
1 kg of CNG	MJ	46,2
1 l of LPG	MJ	25,3

6.3. Energy and emission assessment

The basic computational unit at the micro-level is the network segment travelled by a vehicle during a mission. For each segment the model determines the distance, speed, the current load and the vehicle type, and from these the energy used and the CO_2 emitted. Two energy models are used: a ground-vehicle model for road modes and a momentum-theory model for drones.

For ground vehicles, the consumption rate is interpolated linearly between the empty-load and full-load rates according to the load coefficient defined in Eq. 18. The energy or fuel used on a segment of length d [m] is given by Eq. 19, with the consumption rates expressed per 100 km. The associated CO_2 emission follows from the relevant conversion factor (Eq. 20).

$$\lambda = \frac{\mathrm{currLoad}}{\mathrm{maxLoad}},\ \lambda = 0 \text{ for } \mathrm{maxLoad} = 0 \tag{18}$$

$$U = \left[u_{\mathrm{empty}} + \lambda\left(u_{\mathrm{loaded}} - u_{\mathrm{empty}}\right)\right] \cdot \frac{d}{100000} \tag{19}$$

$$M_{\mathrm{CO_2}} = U \cdot \gamma \tag{20}$$

where:

U - the energy or fuel consumption, e.g. [kWh], [l] or [kg],
Γ - the corresponding CO_2 emission factor,
Λ - the load coefficient,
$u_{\text{empty}}, u_{\text{loaded}}$ - the empty-load and full-load consumption rates.

For non-powered modes (pedestrian, bicycle) both energy use and CO_2 emission are zero.

For drones, a full-mission multirotor model based on momentum theory is used, comprising three phases: vertical climb to the cruise altitude, horizontal cruise, and vertical descent. The cruise and hover powers are derived from the load-interpolated cruise consumption rate (Eq. 21). The climb energy combines the hover power with the potential-energy power required to lift the total mass (Eq. 22), the cruise energy is computed from the cruise consumption rate over the horizontal distance (Eq. 23), and the descent energy is computed from the reduced descent power (Eq. 24) The total drone energy and the corresponding emission are given by (Eq. 25).

$$P_{\text{cruise}} = \frac{c(\lambda)\cdot v_{\text{cruise}}}{100} P_{\text{hover}} = k_{\text{hover}} \cdot P_{\text{cruise}} \tag{21}$$

$$E_{\text{climb}} = \left[P_{\text{hover}} + \frac{m_{\text{tot}}\cdot g\cdot v_{\text{climb}}}{\eta\cdot 1000}\right] \cdot \frac{h}{v_{\text{climb}}} \cdot \frac{1}{3600} \tag{22}$$

$$E_{\text{cruise}} = c(\lambda) \cdot \frac{d_h}{100000} \tag{23}$$

$$E_{\text{descent}} = P_{\text{hover}} \cdot k_{\text{descent}} \cdot \frac{h}{v_{\text{climb}}} \cdot \frac{1}{3600} \tag{24}$$

$$E_{\text{drone}} = E_{\text{climb}} + E_{\text{cruise}} + E_{\text{descent}} M_{\text{CO}_2} = E_{\text{drone}} \cdot \gamma_{\text{elec}} \tag{25}$$

where:
$c(\lambda)$ - the load-interpolated cruise consumption rate,
$v_{\text{cruise}}, v_{\text{climb}}$ - the cruise and climb speeds,
m_{tot} - the take-off mass including the drone and payload,
η - the propulsion efficiency,
h - the cruise altitude,
d_h - the horizontal flight distance,
$k_{\text{hover}}, k_{\text{descent}}$ - the hover and descent power ratios.

The drone model follows the momentum-theory formulation reported in the literature: [16], [8], [1].

The per-mission quantities are accumulated into KPIs per delivery mode and per scenario. The principal indicators are the energy and CO_2 emission normalised per delivered parcel (Eq. 26), and the empty-trip share (Eq. 27), defined as the proportion of transfer (repositioning) missions in the total number of missions. The empty-trip share is a structural indicator of how much vehicle movement is not directly productive.

$$e_{\text{pkg}} = \frac{\sum_i E_i}{\sum_i n_i} \text{co2}_{\text{pkg}} = \frac{\sum_i M_i}{\sum_i n_i} \tag{26}$$

$$\tau = \frac{N_{\text{transfer}}}{N_{\text{total}}} \cdot 100\% \tag{27}$$

where:

e_{pkg} - energy per parcel,

$\mathrm{co2}_{\mathrm{pkg}}$ - emission per parcel,

E_i - energy consumed by the i-th mission,

M_i - emission generated by the i-th mission,

n_i - number of parcels delivered in the i-th mission,

N_{transfer} - number of transfer missions,

N_{total} - total number of missions,

τ - share of transfer missions in all missions,

$1\ \mathrm{kWh} = 3{,}6\ \mathrm{MJ}$ - energy conversion used for reporting energy in megajoules.

6.4. Micro-level scenario experiments and selected results

The active WP2 scenario groups selected for micro-level simulation were executed as simulation experiments, covering BS/AS 1.1, BS/AS 1.2 and BS/AS 1.3. The detailed mapping between D0.3 scenarios and simulation runs is presented in Table 8. Each run produced a complete set of KPI per delivery mode, normalised per delivered parcel, together with the transfer or service distance split and the empty-trip share. The aggregate energy and emission results per scenario are summarised in Table 11.

Table 11. Aggregate energy and emission results per scenario (system level)

Simulation run	D0.3 ref.	Total energy [kWh]	Total CO_2 emission [kg]	Energy /parcel [kWh]	CO_2 /parcel [kg]
FOOD_BS_1_1	BS 1.1	633,64	188,41	0,2862	0,0851
FOOD_AS_1_1_1	AS 1.1.1	419,96	144,74	0,1898	0,0654
FOOD_AS_1_1_2	AS 1.1.2	172,09	95,86	0,0634	0,0353
FOOD_AS_1_1_3	AS 1.1.3	133,19	82,32	0,0491	0,0303
FB_BS_1_2	BS 1.2	217,26	61,36	0,5794	0,1636
FB_AS_1_2_1	AS 1.2.1	125,74	51,04	0,3241	0,1316
FB_AS_1_2_2	AS 1.2.2	132,78	75,48	0,3011	0,1711
FB_AS_1_2_3	AS 1.2.3	123,44	76,29	0,2743	0,1695
PKG_BS	BS 1.3	305,83	89,32	0,1737	0,0507
PKG_AS_1_3_1	AS 1.3.1	217,68	100,33	0,1220	0,0562
PKG_AS_1_3_2	AS 1.3.2	159,38	82,24	0,0896	0,0462
PKG_AS_1_3_3	AS 1.3.3	161,46	92,53	0,0905	0,0518
PKG_AS_1_3_4	AS 1.3.4	267,37	85,01	0,1565	0,0498
PKG_AS_1_3_5	AS 1.3.5	248,65	73,72	0,1408	0,0417
PKG_AS_1_3_6	AS 1.3.6	263,67	89,11	0,1480	0,0500
PKG_AS_1_3_7	AS 1.3.7	413,63	108,97	0,2307	0,0608
PKG_AS_1_3_8	AS 1.3.8	341,21	105,29	0,1907	0,0589
PKG_AS_1_3_9	AS 1.3.9	239,71	72,87	0,1368	0,0416
PKG_AS_1_3_10	AS 1.3.10	151,86	93,85	0,0945	0,0584

Ready-meal delivery shows a clear and monotonic decarbonisation gradient across the scenario series (Fig. 4). Moving from the base scenario BS 1.1 to the zero-emission variant AS 1.1.3, the

CO_2 emission per parcel falls from 0.0851 to 0.0303 kg, a reduction of about 64%, and the energy use per parcel falls from 0.2862 to 0.0491 kWh, a reduction of about 83%. The progression is strictly ordered BS 1.1 > AS 1.1.1 > AS 1.1.2 > AS 1.1.3, even though the two higher variants also carry a 25% increase in demand. This indicates that, in the ready-meal segment, a change in the modal structure of the fleet alone is sufficient to reduce energy intensity substantially, and that the effect is not offset by the higher order volume.

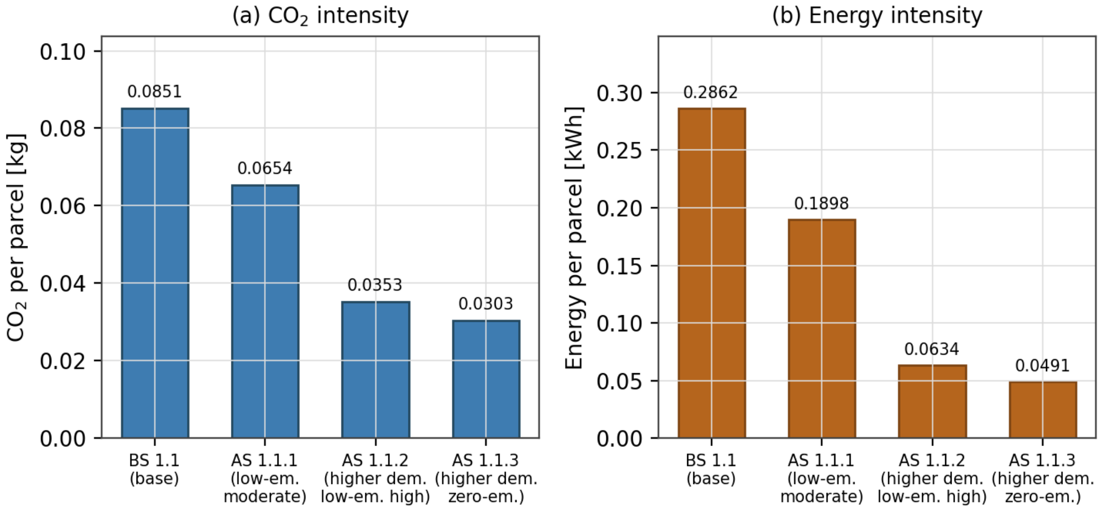

Fig. 4. CO_2 and energy intensity for ready-made food delivery scenarios

The parcel scenarios were used to separate the effect of fleet electrification from the effect of the collection channel (Fig. 5). With the channel structure held at the base mix, progressive electrification reduces energy use per parcel from 0,1737 to about 0,090 kWh, while the CO_2 emission per parcel remains in a narrow band (0,046-0,056 kg). The limited CO_2 response reflects the carbon intensity of the electricity used to displace liquid fuels. With the fleet held at the base configuration, varying the home-vs-locker split produces a non-monotonic pattern: the lowest CO_2 per parcel occurs at the extremes (home 100%: 0.0416 kg; locker 100%: 0,0417 kg) and the highest at the balanced 50/50 split (0,0608 kg). The balanced split combines a substantial number of home deliveries with a substantial volume of client self-pickup trips, so that neither channel is fully consolidated. The drone variants achieve low energy per parcel (direct drone: 0,0945 kWh) but comparatively high CO_2 per parcel (0,0584 kg), because each parcel is served by an individual flight with an empty return leg.

In the case of deliveries to parcel lockers and picking parcels by clients, a key determinant of energy consumption and associated CO_2 emissions is the extent to which recipients use private vehicles for parcel collection. Based on the survey data described in D2.2, the simulation distinguishes between trips made specifically to collect a parcel and trips combined with other activities. In the latter case, the trip is not allocated to the energy consumption or emissions of the distribution system. For intentional collection trips, energy use and emissions also depend on the spatial density of collection points, such as parcel lockers, and on recipients' transport mode choices, including walking, cycling, and motorized travel. These assumptions make it possible to analyze alternative transport behavior scenarios, which may result from differences in infrastructure availability. The function describing the willingness to walk to a parcel locker was derived from the survey data presented in D2.2.

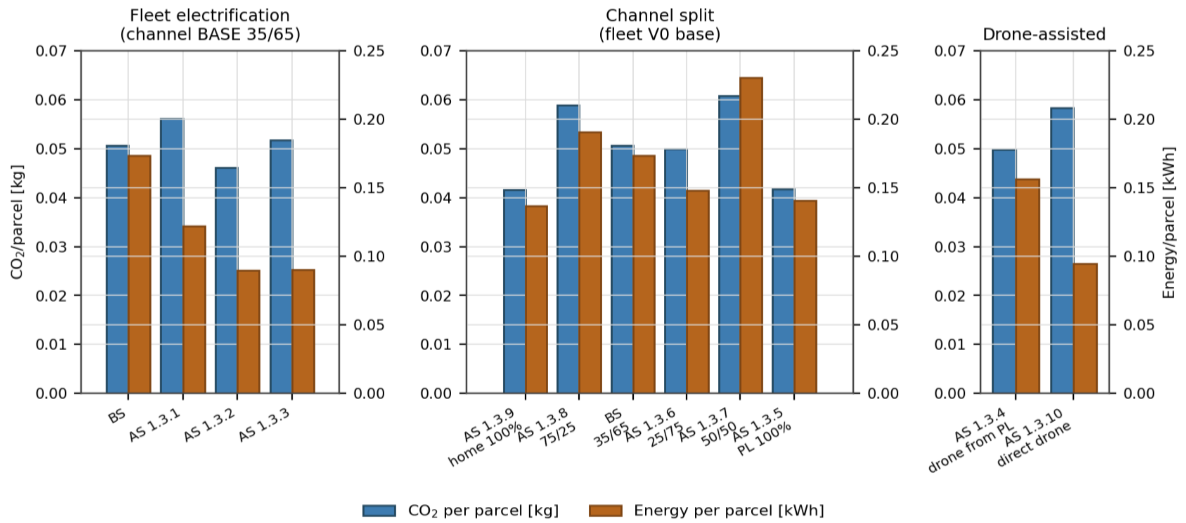

Fig. 5. CO_2 and energy intensity for parcel delivery scenarios

Let d denote the distance to the pickup point. The probability of choosing walking can be written as:

$$P_{\text{walk}}(d) = \min\{1, \max\{0, f(d)\}\} \tag{28}$$

where:

$$f(d) = 0.0766 \cdot e^{-\frac{d}{2000}} + \frac{0.182}{1+e^{\frac{d-401}{31.4}}} + \frac{0.462}{1+e^{\frac{d-792}{32.4}}} + \frac{0.261}{1+e^{\frac{d-1260}{75.9}}} \tag{29}$$

Equivalently, with an explicit restriction to the interval [0, 1]:

$$P_{\text{walk}}(d) = \begin{cases} 0 & f(d) < 0, \\ f(d) & 0 \le f(d) \le 1, \\ 1 & f(d) > 1. \end{cases} \tag{30}$$

Parcel delivery options in which customers collect parcels themselves depend strongly on established customer behavior patterns. This also applies to the composition of the vehicle fleet owned and used by customers for parcel collection. While transport and courier companies make fleet decarbonization decisions on the basis of business plans, expected marketing effects, and regulatory requirements, individual customers determine their vehicle choices through private purchasing and usage decisions, as well as through responses to incentives and programs promoting environmental awareness. The model therefore enables analysis of how these factors affect last-mile delivery performance.

The transfer-to-service distance split (Fig. 6) reveals a structural difference between the delivery modes. Consolidated route-based modes, namely direct courier delivery to the home (LMD_mode = 2) and hub-to-locker delivery (LMD_mode = 3), have no empty repositioning distance in the model, because the served addresses are visited on a single route. In contrast, the modes in which each parcel is handled individually, namely client self-pickup from a locker

(LMD_mode = 4), drone delivery from a locker (LMD_mode = 5) and direct drone delivery (LMD_mode = 6), carry an empty-trip share of about 50%, corresponding to the empty return leg of every individual trip or flight. For these modes the number of trips equals the number of parcels, which raises the energy and CO_2 per parcel relative to the route-based modes. The boxed-meal route (LMD_mode = 7) and the ready-meal courier (LMD_mode = 1) lie between these extremes.

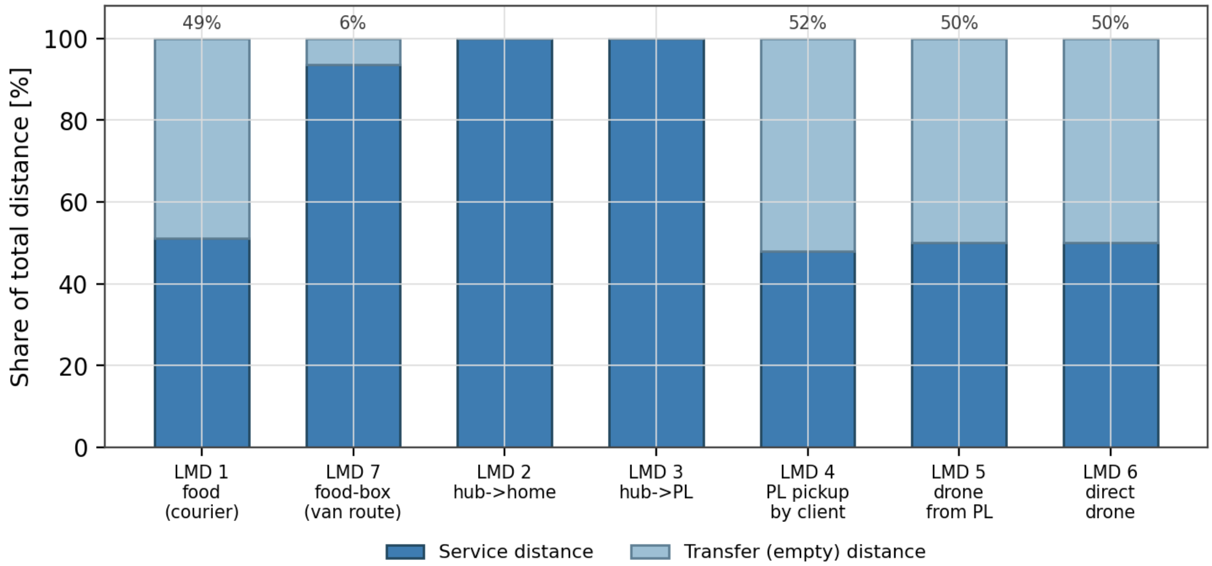

Fig. 6. Service and transfer distance split by last-mile delivery mode

The boxed-meal scenarios behave differently from the ready-meal series. The lowest CO_2 per parcel is obtained for AS 1.2.1 (0.1316 kg), whereas the further variants AS 1.2.2 and AS 1.2.3 show higher CO_2 per parcel (0.1711 and 0.1695 kg) despite a more strongly electrified fleet. This is attributed to the combination of the higher demand multiplier applied in these variants and the small number of missions in the boxed-meal process (18-24 trips per run), which increases the variance of the per-parcel indicators. This result is therefore reported as an indication requiring replication rather than as a stable comparative finding.

The internal structure of the combined parcel base scenario is shown in Table 12, which reports the per-mode results for PKG_BS. The locker supply leg (LMD_mode = 3) is highly consolidated and carries the lowest energy and CO_2 per parcel, the direct home delivery leg (LMD_mode = 2) carries an intermediate value, and the client self-pickup leg (LMD_mode = 4) carries the highest empty-trip share. The combined locker channel (delivery to the locker plus client pickup) is reported jointly to allow a like-for-like comparison with direct home delivery on the same parcel demand. The differences are resulting not only from the structure of fleet owned by suppliers, but also from the structure of the cars owned by clients. The simulator also enables the calculation of additional characteristics for the analyzed variants, including the contribution of individual vehicle types to energy consumption and emissions, delivery time characteristics, and vehicle utilization rates.

Taken together, the experiments confirm that the D0.3 scenarios were realised in the simulation and that they produce useful, internally consistent and interpretable indicators. The simulation model developed for micro-level analysis of last-mile processes is fully configurable and can be applied to different delivery types under a wide range of operating conditions. These conditions can be parameterized using survey results, industry data, and open data sources, such as OpenStreetMap. The scenario set presented in this chapter is based on data from the sources discussed above and enables testing of the organizational and technological concepts developed in the remaining work packages of the project. Results obtained from the micro-scale model for homogeneous regions can subsequently be used as inputs to higher-level models.

Table 12. Selected per-mode results for the parcel base scenario PKG_BS

Delivery mode (LMD)	Trips	Parcels	Energy [kWh]	CO_2 [kg]	Empty [%]
2 – direct home delivery	17	747	201,63	56,55	0
3 – hub to parcel locker	6	1014	40,24	14,65	0
4 – client pickup from locker	331	331	63,95	18,12	52,0
3+4 – combined locker channel	-	-	104,20	32,77	-
General for scenario	-	-	305,83	89,32	-

The results identify several mechanisms relevant to the energy assessment of last-mile delivery: the strong response of the ready-meal segment to fleet decarbonisation, the dependence of the parcel channel on the degree of consolidation rather than on the channel label alone, the structural penalty of individual-trip modes through their empty return legs, and the trade-off between the low flight energy and the elevated per-parcel emission of drone delivery.

Two methodological caveats apply. First, the route optimisation is stochastic (random shaking in the VNS and random fleet selection), so the reported values are single-run estimates; for publication-grade conclusions the experiments require replication with different random seeds and an analysis of variance. Second, the boxed-meal and parcel processes generate a small number of missions per run, which increases the sensitivity of the per-parcel indicators to randomness. The results should therefore be read as evidence of mechanisms, tendencies and relations rather than as definitive values for a specific operator or network, in line with the interpretation adopted throughout D2.3. The detailed numerical results, the full experiment settings and the model validation are presented in the related publication [6]; the methodology of fleet-related emission simulation is documented in [21].

6.5. Contribution to D2.3 and further integration

The micro-level part of the research provided an operational tool for assessing individual last-mile delivery processes in terms of energy use and CO_2 emissions. It demonstrated that the scenarios identified in D0.3 are simulation-ready and that they yield comparable KPI across delivery modes and organisational variants, computed on a common energy and emission basis.

The most important value of the micro level is the ability to attribute differences in energy intensity to specific organisational and technological factors: fleet composition, collection channel, degree of consolidation and the use of drones. This complements the macro level, which establishes the scale and spatial distribution of impacts, by explaining the operational mechanisms that generate them.

The KPI produced at the micro level form the basis for further integration within D2.3. They serve as the reference-zone results that the KPI-scaling approach (Chapter 7) transfers to similar TAZs, and as the channel-level energy intensities used in the SD model of the parcel-delivery channels (Chapter 8). In this way the micro level functions as the operational layer of the multi-level modelling framework documented in D2.3 and contributes the process-level evidence required for the policy-oriented interpretation at milestone M2.

7. Macro-micro integration for KPI scaling

7.1. Purpose and methodological background of KPI scaling

The integration of the macroscopic and microscopic levels was applied in D2.3 to develop an approach for estimating last-mile delivery KPIs across a larger urban area without the need to conduct a full microsimulation for every TAZ. The underlying assumption is that TAZs with similar spatial, demographic, transport-related, and functional characteristics may generate comparable operational patterns of B2C deliveries. Consequently, detailed microsimulation can be performed for selected reference TAZs, while KPI values for the remaining TAZs can be estimated using scaling functions. The general concept of this approach is presented in Figure 7.

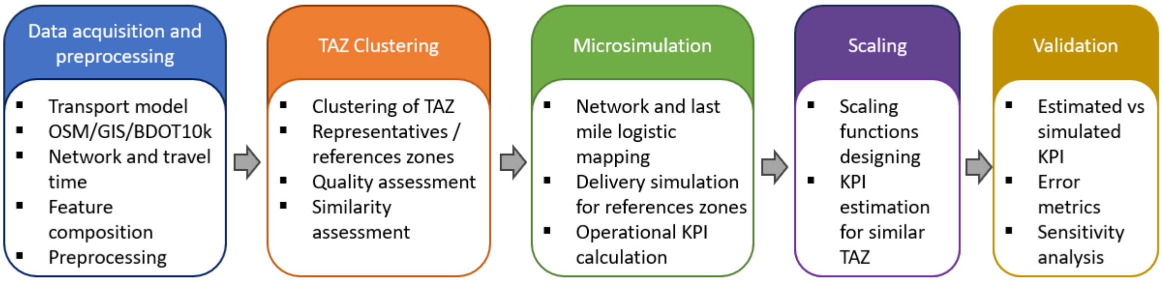

Fig. 7. General framework for macro-micro integration and KPI scaling

The starting point for this component of the research was the initial work on modelling operational and fleet-related decisions using the FlexSim environment, combined with the assessment of pollutant emissions. In publication [21], a simulation-optimisation model was developed for assigning vehicles and drivers to service areas, in which micro-level operational decisions were evaluated against both economic and environmental criteria. The model employed FlexSim and OptQuest to search the solution space, followed by COPERT to estimate emissions of selected pollutants.

The results revealed a clear trade-off between economic and environmental objectives. Solutions that maximised company profit were associated with higher external emission costs, whereas more environmentally favourable variants required the acceptance of lower economic performance. In one of the analysed variants, adopting an intermediate solution reduced the external cost of CO_2 emissions by more than 41%, while decreasing profit by approximately 12%.

The relevance of this stage to D2.3 lies in demonstrating that decisions made at the microscopic level, such as vehicle selection, driver assignment, the characteristics of the service area, task execution, and fleet composition, can be formalised and assessed using measurable KPIs. At the same time, the findings highlighted a limitation of conventional micro-level analyses. Although such analyses provide valuable and detailed results, their direct extension to large urban areas would require considerable computational and analytical effort. The subsequent step therefore involved the development of a method capable of combining the operational detail of microsimulation with the spatial coverage of a macroscopic model.

In the approach adopted in D2.3, the macroscopic model developed in PTV Visum provides a consistent division of the study area into TAZs, together with data on the transport network, traffic conditions, spatial structure, and trip purposes. Microsimulation, conducted for selected zones, generates detailed KPIs describing the delivery process. Scaling functions integrate these two analytical levels and enable KPI values to be estimated for zones exhibiting characteristics similar to those of the reference zones.

Preliminary research on the feasibility of scaling selected KPIs was presented in publication [22], while the applicability of clustering methods in this context was examined in publication [12]. A comprehensive assessment of method selection and a broader analysis of scaling functions were developed in the associated KPI-scaling study [18].

7.2. TAZ similarity, clustering and reference-zone selection

The scaling of KPIs is based on determining the degree of similarity between TAZs. Each TAZ was characterised using a set of variables reflecting its demand potential, spatial structure, traffic conditions, network configuration, and urban functions. In the initial stage of the research, trip-purpose data derived from the macroscopic model were used, including information on home-based trips, work-related trips, trips associated with other activities, and freight movements.

On this basis, the TAZs were clustered and the appropriate number of clusters for GZM was examined. Publication [12] evaluated solutions ranging from 3 to 50 clusters. The results indicated that the largest reduction in dissimilarity occurred when increasing the number of clusters from 3 to 10. Between 10 and 20 clusters, the improvement became more gradual, while beyond 30 clusters the benefits of further subdivision were limited. The study applied the Euclidean distance between the feature vector of a given zone and the corresponding cluster centroid, as expressed in Eq. 31:

$$D(A_z, A_c) = \sqrt{\sum_{k=1}^{K} (A_z(k) - A_c(k))^2} \tag{31}$$

where:
A_z - vector of features of the z-th TAZ,
A_c - vector of features of the TAZ representing the centroid of the c-th cluster,
K - number of features included in the analysis.

The spatial results obtained for solutions comprising 10 and 20 clusters demonstrated that a smaller number of clusters produces a more synthetic and urbanistically interpretable spatial classification, whereas a larger number of clusters provides a more detailed representation of spatial differentiation. This observation was relevant to the subsequent stages of the research, as KPI scaling requires a balance between the quality of the classification, the interpretability of the clusters, and the number of TAZs for which detailed microsimulation must be conducted.

In the extended KPI estimation procedure developed in the associated KPI-scaling study [18], the set of variables used to characterise the TAZs was broadened to include demographic, network-related, traffic-related, trip-purpose, spatial, and functional characteristics. The initial dataset comprised 880 TAZs within the GZM area. Following the application of a minimum-population threshold, 811 zones were retained for further analysis. This criterion reflected the nature of the problem under investigation, namely B2C courier deliveries, for which households constitute the principal source of demand. The characteristics of the datasets are presented in Table 13.

The data were prepared using several alternative attribute compositions. Both extended and reduced variable sets were tested, together with variants incorporating logarithmic transformations of selected density-based variables. Z-score standardisation and robust scaling were applied. The inclusion of alternative preprocessing procedures was necessary because TAZ characteristics are expressed in different units and exhibit different value ranges and statistical distributions. Moreover, some variables, including population density, road density, the floor area ratio (FAR), and the land use mix index (LUMI), may be characterised by highly skewed distributions.

Table 13. Data groups used for TAZ clustering

Data category	Example variables	Relevance to KPI scaling
Demographic	Population, population density	Potential for generating B2C delivery demand
Network-related	Road density, node density, total network length	Spatial accessibility and complexity of delivery operations
Traffic-related	Volume-to-capacity ratio, travel times	Traffic conditions affecting delivery time and energy consumption
Trip-purpose-related	Work, school, university, other activities, freight	Functional profile of the TAZ
Spatial and functional	FAR, shares of residential, service, and industrial land use, LUMI	Urban morphology and land-use structure
Logistics-related	Parcel lockers, postal service points, collection infrastructure	Capacity to support out-of-home (OOH) deliveries

An additional aspect examined in one of the research variants involved the application of a similarity matrix combining zone characteristics with transport relationships between zones. In general form, the matrix can be expressed as follows (Eq. 32):

$$S = \alpha S_X + (1 - \alpha) S_T \quad (32)$$

where:
S - final similarity matrix,
S_X - feature-based similarity matrix,
S_T - similarity matrix based on travel times between TAZs,
α - weight assigned to the feature-based component.

Figure 8 presents an illustrative clustering of the TAZs, showing their distribution across groups for a selected set of characteristics, clustering method, and number of clusters (k-means, k=3, k=15). A pronounced imbalance can be observed in the allocation of TAZs among the clusters. This may indicate insufficient differentiation between the zones or limitations in the scope and discriminatory power of the available data. Such an imbalance may also affect the values and interpretation of the clustering quality measures.

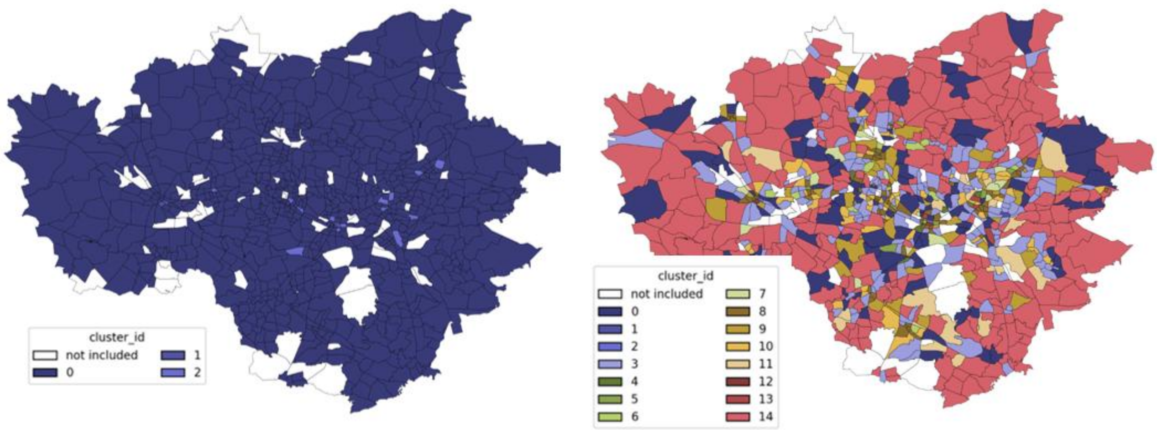

Fig. 8. Examples of TAZ clustering for different numbers of clusters

7.3. Clustering experiments and interpretation of results

Several clustering methods were compared within the KPI scaling procedure: k-means, k-medoids, hierarchical clustering, Gaussian mixture models, spectral clustering, and Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). This selection made it possible to examine classical distance-based algorithms alongside probabilistic, spectral, and density-based approaches. For methods requiring the number of clusters to be specified in advance, selected values of (k) were analysed. In the case of HDBSCAN, the number of clusters was determined by the algorithm parameters and the underlying structure of the data. An overview of the methods examined is provided in Table 14.

Table 14. Clustering methods examined in the KPI scaling procedure

Method	Characteristics	Role in the study
K-means	Centroid-based method that minimises within-cluster deviations from cluster centroids	Baseline partitioning approach
K-medoids	Partitioning method in which each cluster is represented by an actual zone	Greater robustness to outliers
Hierarchical clustering	Agglomerative method that constructs a hierarchy of clusters	Assessment of clustering stability and interpretability
Gaussian Mixture Model (GMM)	Probabilistic model based on a mixture of Gaussian distributions	Assessment of soft cluster assignments
Spectral clustering	Method based on a similarity matrix	Integration of TAZ characteristics and interzonal travel times
HDBSCAN	Density-based method that does not require the number of clusters to be specified in advance	Identification of irregular cluster structures and atypical observations

The silhouette coefficient was adopted as the primary measure of clustering quality. For the z-th TAZ, it can be expressed as follows (Eq. 33):

$$s(z) = \frac{b(z) - a(z)}{\max(a(z), b(z))} \tag{33}$$

where:
$a(z)$ - mean distance between the z-th TAZ and all other TAZs assigned to the same cluster,
$b(z)$ - minimum distance between the z-th TAZ and the TAZs assigned to any other cluster.

Table 15 summarises selected clustering quality results obtained for the analysed methods. The highest and most stable silhouette coefficient values were achieved by hierarchical clustering, k-medoids, and k-means. For the best-performing configurations, the silhouette coefficient reached approximately 0,87 for k-means, 0,92 for k-medoids, and 0,95 for hierarchical clustering. The Gaussian Mixture Model performed substantially less favourably in terms of cluster separation, although the AIC and BIC criteria could still indicate an acceptable statistical fit. Spectral clustering produced moderate results, but remained methodologically informative because of its capacity to integrate feature-based similarity with transport relationships. HDBSCAN achieved its best performance under the Excess of Mass (EOM) cluster selection method; however, its results were more variable and strongly dependent on parameter settings.

An important methodological finding was that increasing the number of variables did not automatically improve clustering quality. The full dataset did not provide a clear advantage over more compact and interpretable variable sets. The most favourable results were obtained for variants based on a carefully selected combination of demographic, network-related, trip-purpose, and spatial-functional characteristics. It was also found that the logarithmic transformation of density-based variables improved the structure of the data for several clustering methods.

Table 15. Synthetic summary of the TAZ clustering quality results

Method	Best observed clustering quality result - silhouette coefficient	Interpretation for KPI scaling
K-means	~0,87	A robust baseline method that is transparent and easy to interpret
K-medoids	~0,92	Very good performance; the cluster representative is an actual TAZ
Hierarchical clustering	~0,95	Highest cluster separation quality, although cluster sizes may be uneven
GMM	~0,15	Poor cluster separation despite the formal statistical fit of the model
Spectral clustering	~0,46	Moderate performance, but capable of incorporating spatial and transport relationships
HDBSCAN	~0,74	Useful when applying the EOM cluster selection method, but more sensitive to parameter settings and data structure

From the perspective of KPI scaling, clustering quality alone is not a sufficient criterion for method selection. Very high silhouette coefficient values may result from a division into a small number of large and well-separated groups that are easy to interpret, but not necessarily optimal for the accurate estimation of KPIs. An example is the k=3 solution obtained using k-means, as shown in Fig. 8, in which the distribution of TAZs among clusters is highly imbalanced. Conversely, more balanced clusters may yield lower silhouette coefficient values while providing a more suitable basis for selecting reference and validation TAZs. Therefore, the subsequent procedure jointly assessed clustering quality, the interpretability of the selected features, the distribution of cluster sizes, and the accuracy of KPI scaling.

Two feature sets were selected for the subsequent scaling analyses. The first represented a compact and readily interpretable feature structure, whereas the second was used to assess the influence of transformations applied to density-based variables on clustering quality and estimation accuracy. For the selected methods, values of (k=2, 3, 5, 10,15) were tested. In the case of HDBSCAN, a more conservative configuration based on the EOM cluster selection method was applied.

7.4. Microsimulation and KPI scaling functions

The microsimulation of B2C courier deliveries serves as the source of reference KPI values within the scaling procedure. For selected zones, a local representation of the transport network is developed, parcel demand is generated, courier routes are determined, and operational, energy-related, and environmental indicators are subsequently calculated. This makes it possible to reproduce local differences arising from network configuration, building distribution, the number of delivery points, demand levels, and service parameters.

Publication [22] applied an approach in which the PTV Visum model and GIS data served as sources of macroscopic input data, while FlexSim was used to simulate deliveries within the reference TAZ and other similar TAZs. Three scenarios were analysed: direct home delivery, delivery to a parcel locker, and drone-based delivery from a parcel locker to the final recipient. The indicators considered included courier delivery time, courier travel distance, drone operating time, drone delivery time, and drone travel distance.

The extended research procedure presented in the associated KPI-scaling study [18] employed a B2C courier delivery model formulated as an open multiple travelling salesman problem (open mTSP). Vehicles begin their routes at a designated entry point to the zone, serve the assigned delivery locations, and do not return to the starting point after completing their tasks. The A* algorithm was used to determine shortest paths within the local network, while a VNS algorithm was applied to vehicle routing. The model incorporated, among other factors, a constraint on the number of parcels assigned to each route, service time at each delivery point, traffic conditions, and the structure of the local transport network.

The output of the microsimulation is a set of KPIs that can be expressed in general form as shown in Eq. 34. In addition, unit indicators are calculated per unit of freight handled.

$$K_z = [T_z, T_z^{drive}, D_z, F_z, E_z] \tag{34}$$

where:
T_z - total delivery time in the z-th TAZ,
T_z^{drive} - total driving time in the z-th TAZ,
D_z - total distance travelled in the z-th TAZ,
F_z - fuel consumption in the z-th TAZ,
E_z - energy consumption in the z-th TAZ.

Scaling functions are used to estimate KPI values for a z-th TAZ on the basis of the value obtained for a reference zone (r_c) belonging to the same cluster, as expressed in Eq. 35:

$$\widehat{K}_{z,kpi} = K_{r_c,kpi} \cdot f_{kpi}(z, r_c) \tag{35}$$

where:
$\widehat{K}_{z,m}$ - estimated value of a given KPI for the z-th TAZ,
$K_{r_c,m}$ - value of the KPI obtained from microsimulation for the reference zone,
$f_m(z, r_c)$ - scaling function.

Four groups of scaling functions were applied in the study (Table 16). The first group comprised ratio-based functions using relationships between the basic characteristics of the TAZs. The second group consisted of functions inspired by the Beardwood-Halton-Hammersley (BHH) relationship, according to which route length in routing problems increases approximately in proportion to the square root of the product of the number of service points and the area of the zone. The third group included functions adjusted for clustering quality, while the fourth comprised functions corrected for the similarity between the target zone and the cluster representative.

Table 16. Groups of KPI scaling functions

Group of functions	Example functions	Rationale for the formulation of the function
P1	GeoMean, Morphology, NetworkTraffic	Scaling based on ratios between the basic characteristics of the TAZs
P2	BHH_Basic, BHH_Morph, BHH_Traffic	Use of relationships between demand, zone area, and route length
P3	Sil_NetworkTraffic, Sil_BHH_Traffic	Greater confidence in the scaling function for clusters of higher quality
P4	Sim_NetworkTraffic, Sim_BHH_Traffic	Greater confidence in the scaling function when the target TAZ exhibits greater similarity to the cluster representative

7.5. Validation, sensitivity analysis and selected results

The scaling functions were validated by comparing the estimated values with those obtained from microsimulation for the validation TAZs. For each configuration, defined by the dataset, clustering method, number of clusters, scaling function, and KPI, error measures were calculated, including the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Weighted Absolute Percentage Error (WAPE). Particular emphasis was placed on WAPE, as it is less sensitive than conventional MAPE to very small denominator values.

For a given KPI evaluated across the set of validation TAZs, the WAPE measure can be expressed as follows (Eq. 36):

$$\widehat{K}_{z,kpi} = K_{r_c,kpi} \cdot f_{kpi}(z, r_c) \tag{36}$$

where:
$K_{z,kpi}$ - value of KPI obtained from microsimulation for the z-th TAZ,
$\widehat{K}_{z,kpi}$ - value of KPI estimated using the scaling function for the z-th TAZ,

In the pilot study presented in publication [22], validation was conducted using one reference TAZ and three similar TAZs selected according to three alternative similarity specifications: spatial and trip-purpose data, energy consumption data, and postal infrastructure data. The highest estimation accuracy was obtained for the variant based on a composite vector of spatial and trip-purpose characteristics, combined with scaling by population. In this variant, the mean MAPE was approximately 12%. The second-best result was achieved by the model based on postal infrastructure and scaling by road-network length, for which the MAPE was approximately 25%. A synthesised overview of the validation results is presented in Table 17.

The extended KPI-scaling study [18] indicates that the best-performing scaling functions may vary depending on the type of KPI considered. Based on the WAPE measure, functions derived from the BHH relationship achieved very good results for indicators associated with travel distance, fuel consumption, and energy consumption, particularly the BHH_Morph variant. For some KPIs, the best-performing configurations yielded WAPE values of approximately 0,06-0,10.

Table 17. Validation results of the approach in the pilot study

Similarity variant	Attributes	Scaling function	Mean MAPE	Interpretation
V1	Spatial characteristics and trip purposes	Population	Approx. 12%	Best agreement with the microsimulation results
V2	Energy consumption by vehicle type	Population or road-network length	60-100%	Energy-related characteristics alone were insufficient to reproduce the delivery process
V3	Postal infrastructure	Road-network length	Approx. 25%	Acceptable result, although clearly less accurate than V1

Time-related indicators, particularly total route time, proved more difficult to estimate and were associated with higher error values. This is consistent with the characteristics of the delivery process: travel distance and energy consumption are strongly related to spatial scale and demand, whereas time is more sensitive to the local network structure, route organisation, service times, congestion, and operational constraints. A synthesised overview of the results is presented in Table 18.

Table 18. Synthesised overview of KPI scaling results

KPI group	Best-performing approaches	Typical range of the lowest WAPE values	Interpretation
Route distance	BHH-based functions, particularly BHH_Morph	Approx. 0,06-0,10	Distance can be scaled effectively using demand, zone area, and urban morphology
Fuel and energy consumption	BHH-based functions and functions adjusted for traffic conditions	Approx. 0,06-0,10	Energy consumption is strongly associated with travel distance and the structure of delivery operations
Driving time	BHH-based functions and NetworkTraffic functions	Approx. 0,06-0,13	Driving time is scalable, but traffic conditions must be incorporated
Total route time	Morphology- and traffic-based functions	Approx. 0,15-0,20 or higher	This indicator is strongly dependent on local service times and route organisation
Unit KPIs per parcel	Functions derived from those used for total KPIs	Dependent on the stability of demand	Interpretation requires caution when demand values are low

The conclusions derived from the WAPE analysis are methodologically significant. More complex scaling functions did not consistently outperform simpler alternatives; however, variants incorporating the BHH relationship and TAZ morphology frequently produced very good results. This indicates that, in the context of B2C deliveries, not only demographic characteristics but also the relationship between the number of delivery points, TAZ area, and the spatial structure of the built environment are of fundamental importance.

A sensitivity analysis was also conducted with respect to changes in courier vehicle capacity. Such changes directly affect the number of routes, route lengths, delivery times, and the overall structure of service operations. This type of analysis makes it possible to determine whether the scaling functions remain stable when the organisation of the delivery system changes. For functions requiring calibration, one operational variant was used as the calibration case, while a second variant was employed to verify the stability of the estimation error.

This issue is particularly relevant from the perspective of practical applications, as operational parameters in real-world distribution systems, including vehicle capacity, the number of couriers, demand structure, and service time, may vary over time. The analysis indicated a high degree of stability in KPI scaling, with WAPE values remaining at a comparable level across the analysed operational variants.

7.6. Contribution to D2.3 and relation to other modelling streams

The KPI scaling approach constitutes the central component of macro-micro integration in D2.3. The macroscopic model provides data on TAZs, network structure, traffic conditions, travel times, and area characteristics. Microsimulation generates detailed KPI values for selected reference TAZs. Clustering and scaling functions enable these results to be transferred to similar TAZs, thereby reducing the number of microsimulation experiments required.

The principal value of this approach lies in extending the results of individual microsimulation experiments to the assessment of a larger urban area. In practical terms, it eliminates the need to construct a detailed model for every TAZ. Instead, clusters of similar zones can be identified, microsimulation can be conducted for selected cluster representatives, and KPI values can subsequently be estimated for the remaining TAZs. This reduces the analytical workload, shortens the time required for the assessment, and enables a larger number of scenario variants to be examined. In the future, the approach may also support the transfer of results to other cities and the development of a universal repository of reference patterns.

From the perspective of WP2 as a whole, this approach contributes to the objective of developing scalable methods for the energy-related and operational assessment of urban freight distribution systems. Chapter 5 describes the macroscopic layer, which enables the spatial distribution of energy consumption, emissions, and transport-related burdens to be identified. Chapter 6 presents the microsimulation layer, in which detailed last-mile delivery processes are analysed. Chapter 7 subsequently demonstrates how micro-level results can be applied at a broader spatial scale by means of TAZ similarity and scaling functions.

8. Macro-micro integration for system dynamics

8.1. System Dynamics as a framework for analysing urban logistics systems

SD was employed in D2.3 as an approach for analysing urban logistics as a system of interconnected processes whose effects unfold over time. In contrast to macroscopic modelling, which enables the spatial distribution of traffic, energy consumption, and emissions to be determined, and microsimulation, which represents detailed operational processes, SD focuses on causal relationships, time delays, the accumulation of effects, and feedback loops. This is particularly relevant to urban logistics, where the consequences of organisational and infrastructural changes do not result from a single decision alone, but depend on the responses of logistics operators, recipients, infrastructure, and the transport system.

Many phenomena within last-mile systems are inherently dynamic. An increase in the volume of B2C parcels raises the operational burden on logistics operators, intensifies the use of fleets and point-based infrastructure, affects the degree of delivery consolidation, and may lead to the overloading of selected service channels. The development of out-of-home solutions, such as Automated Parcel Machines (APMs) and PUDO points, improves consolidation opportunities for operators, but simultaneously transfers part of the delivery process to recipients. Parcel collection may be undertaken on foot, by bicycle, by public transport, by car, or as part of another journey. Consequently, the actual energy balance of the system depends not only on courier vehicle activity, but also on recipient behaviour and the manner in which logistics infrastructure is used.

In this context, research on travel induced by parcel collection from APMs constituted an important foundation for the application of SD. Publication [13] demonstrated that the assessment of APMs should not be limited to analysing reductions in courier vehicle activity resulting from delivery consolidation. It should also account for the additional mobility of recipients, which depends on parcel locker locations, the spatial distribution of residents, acceptable walking time, parcel collection frequency, the share of dedicated trips, and modal split. The results showed that, in urban areas, most residents are located within an acceptable walking distance of a parcel locker, whereas in less urbanised areas a larger proportion of households may be located beyond such a distance, thereby increasing the probability of car-based collection trips.

System Dynamics extends this analytical logic by incorporating the temporal dimension and interactions between variables. Recipient mobility is therefore not treated as a fixed external parameter, but as a component linked to infrastructure density, spatial accessibility, parcel collection time, APM capacity utilisation, and parcel redirection. This framework makes it possible to investigate the conditions under which APMs genuinely improve the energy efficiency of last-mile delivery, as well as those in which their positive effects may be reduced by additional car journeys, insufficient locker turnover, or an inappropriate density of the APM network.

A general SD model of urban logistics may comprise several interdependent subsystems, as presented in Table 19: delivery demand, the structure of distribution channels, courier fleets and operations, logistics infrastructure, recipient behaviour, traffic conditions, energy consumption, emissions, and urban policy instruments. The identification of feedback loops is of particular importance. For example, an increase in demand may intensify the use of fleets and infrastructure and, in the absence of sufficient capacity, result in delays, parcel redirection, or a deterioration in service quality. Conversely, higher demand may improve unit-level efficiency if it enables greater delivery consolidation. Similarly, an increase in the number of collection points may reduce recipient travel distances, while simultaneously increasing the fixed energy consumption of the supporting infrastructure.

Table 19. Application of System Dynamics to the analysis of urban logistics

Area of SD application	Example variables	Type of relationship analysed
Delivery demand	Parcel volumes, seasonality, e-commerce growth, shares of delivery channels	Effects of increasing demand on system load
Logistics infrastructure	APMs, PUDO points, microhubs, capacity, network density	Relationship between spatial accessibility and service capacity
Courier operations	Number of routes, consolidation, service frequency, fleet composition	Effects of delivery organisation on energy consumption and service quality
Recipient behaviour	Modal split, trip chaining, dedicated trips, parcel collection time	Influence of user behaviour on the net energy balance
Energy and emissions	Vehicle energy consumption, infrastructure energy consumption, local emissions	Assessment of technological and organisational impacts
Urban policies	Low-emission zones, access restrictions, support for OOH delivery, charging infrastructure	Effects of regulatory measures on operator and recipient behaviour

Fig. 9 presents a simplified causal feedback structure of an urban logistics system. The diagram links customer-related drivers, such as e-commerce intensity, active customer base and delivery behaviour, with parcel demand, operator capacity, fleet operations, service quality and infrastructure development. It also shows how out-of-home delivery infrastructure, including OOH, PUDO and APM networks, affects recipient travel distance and car-based pickup trips, which in turn influence energy use and emissions.

The diagram also highlights the role of city policy and regulatory support as an integrating factor. Policy measures may support logistics infrastructure capacity, charging infrastructure availability and fleet electrification, while the observed level of energy use, emissions and service quality can create feedback pressure for further regulatory or organisational changes. The presented diagram should be interpreted as a general system-level representation of feedback relations in urban logistics.

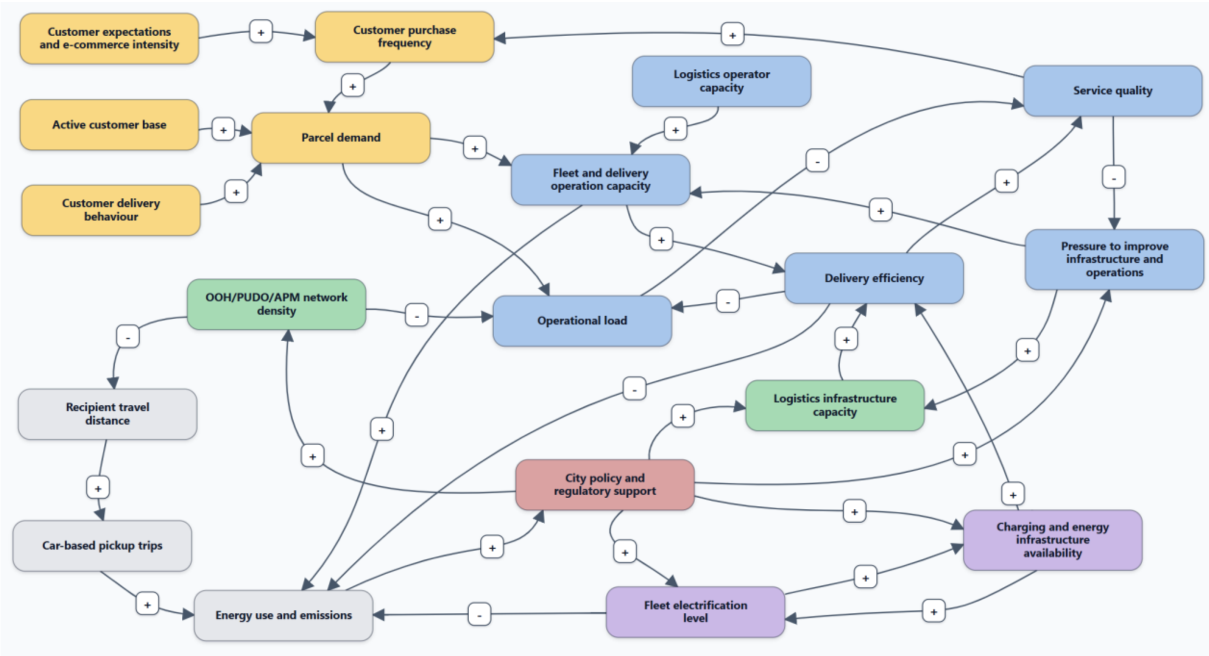

Fig. 9. Causal feedback diagram for urban logistics system dynamics

8.2. System Dynamics-based analysis of APM, PUDO and HOME delivery channels

Within D2.3, the SD approach was applied to a selected component of urban last-mile logistics comprising three delivery channels: HOME, PUDO, and APM. The objective of the study was to determine how changes in the distribution of demand among delivery channels, overall demand levels, APM density, locker turnover, and recipient behaviour affect the energy balance of the system. Particular attention was devoted to the APM channel, as it effectively illustrates the complexity of the relationships between operator-side consolidation benefits, spatial accessibility, recipient mobility, and the energy consumed by the supporting infrastructure. Detailed results of this research are presented in the associated System Dynamics study [17].

The detailed case study was conducted for the GZM area. The model incorporated 162 APMs operated by a leading service provider, with an average of 97 compartments per machine, and a study area of 164,51 km². Three levels of daily demand were considered: 28 675, 33 101, and 42 899 parcels. The model also accounted for the operator's market share, the share of the out-of-home delivery channel, the proportion of APM deliveries within the OOH channel, failed-delivery rates, the average parcel dwell time in a compartment, APM replenishment frequency, the average number of parcels delivered during a single APM service visit, and the proportion of parcel collections undertaken as part of trip chaining. The principal model parameters therefore included daily parcel demand, the number and capacity of APMs, average compartment occupancy time, trip-chaining behaviour, HOME and APM delivery parameters, and failed-delivery rates.

The model was structured around three interconnected subsystems. The first represents the allocation of demand among the HOME, PUDO, and APM delivery channels. The second describes the APM infrastructure, including the number of machines and compartments, compartment occupancy, available capacity, replenishment rates, parcel collections, redirections, and overflow to PUDO points. The third comprises the energy component, accounting for the energy consumed by couriers serving the individual delivery channels, the energy associated with additional recipient journeys to APMs, and the operational energy consumption of the APM infrastructure.

The model also incorporates a parcel-redirection mechanism activated when APM capacity utilisation is high, as well as the possibility of transferring a proportion of parcels to PUDO points when the receiving capacity of the APM network is exceeded. The principal assumptions adopted in the study are summarised in Table 20.

Table 20. Principal assumptions of the SD model for the HOME-PUDO-APM delivery channels

SD component	Elements	Application
Delivery channels	HOME, PUDO, APM	Comparison of alternative parcel delivery and collection channels
Demand	Three levels: minimum, average, and maximum	Representation of variations in parcel volumes
APM infrastructure	Number of machines, number of compartments, network density	Representation of capacity constraints and spatial accessibility
Parcel turnover	Average parcel dwell time in a compartment	Assessment of the influence of recipient behaviour on system utilisation
Compartment replenishment	Frequency of APM servicing by couriers	Assessment of the influence of courier operations on effective system capacity
Recipient mobility	Share of car journeys, trip chaining, distance to the APM, share of dedicated trips	Assessment of whether courier-side consolidation benefits are offset by additional recipient journeys
Energy	Courier vehicles, recipients' cars, APM infrastructure energy consumption	Integrated energy assessment of the delivery channels

The incorporation of recipient mobility into the SD model was directly linked to the previously developed model of travel induced by parcel collection from APMs. In that approach, additional car journeys were estimated by combining survey data on recipient preferences with a spatial analysis of population and APM locations, as well as modal split data derived from the macroscopic GZM model. The analysis accounted, among other factors, for the number of parcels collected, the share of parcels delivered to APMs, the proportion of journeys undertaken exclusively for parcel collection, and the probability of choosing a motorised mode depending on walking time. In the SD model, this logic was extended by linking the number of APMs, network density, recipient travel distance, the share of car-based journeys, and recipient energy consumption.

Another important component was the representation of the relationship between APM network density and spatial accessibility. Spatial analyses were used to determine the relationship between the number of APMs and the population-weighted distance to the nearest machine, as well as the distance between individual APMs. A function describing the share of car journeys to APMs as dependent on travel distance was also incorporated. This formulation makes it possible to analyse a typical infrastructure-related trade-off: increasing the number of APMs improves accessibility and reduces the share of car-based collection journeys, but simultaneously increases the fixed component of energy consumption associated with operating the machines.

8.3. Selected scenario results and interpretation

The SD model was applied to assess a baseline configuration and a set of sensitivity scenarios. The baseline variant was used to determine the structure of energy consumption across the HOME, PUDO, and APM delivery channels under three demand levels. The results indicated that total energy consumption increased with parcel volume, whereas energy consumption per successfully delivered parcel remained relatively stable. For the system as a whole, this value amounted to approximately 1,21 MJ per parcel.

However, substantial differences were observed between the individual delivery channels. The HOME channel was characterised by energy consumption of approximately 2,406 MJ per parcel. By contrast, the APM channel, accounting jointly for infrastructure energy consumption, courier operations, and recipient mobility, achieved approximately 0,199 MJ per parcel under minimum demand, 0,192 MJ per parcel under average demand, and 0,184 MJ per parcel under maximum demand. Selected results are summarised in Table 21.

Table 21. Selected baseline results of the SD model

Indicator	Min	Avg	Max
Number of parcels in the system [parcels/day]	28 675	33 101	42 899
Successfully delivered HOME parcels [parcels/day]	11 558,7	13 342,8	17 292,3
Successfully delivered PUDO parcels [parcels/day]	1 051,2	1 213,5	1 572,6
Successfully delivered APM parcels [parcels/day]	12 367,2	14 276,1	18 501,9
HOME energy consumption [MJ/day]	27 815,7	32 109,1	41 613,5
HOME energy consumption [MJ/parcel]	2,406	2,406	2,406
Total APM energy consumption [MJ/day]	2 464,0	2 739,9	3 400,1
Total APM energy consumption [MJ/parcel]	0,199	0,192	0,184
Total system energy consumption [MJ/day]	30 327,2	34 901,2	45 076,0
Total energy consumption [MJ/parcel]	1,214	1,211	1,206

These results demonstrate two important mechanisms. First, the APM channel exhibits a favourable energy profile on a per-parcel basis because delivery consolidation reduces courier vehicle activity. Second, as demand increases, the unit energy efficiency of the APM channel improves because the fixed energy consumption of the infrastructure is distributed across a larger number of parcels. This scale effect persists only until the system approaches its capacity limits. Once demand exceeds service capacity, congestion, parcel redirection, and the transfer of a proportion of parcels to alternative delivery channels occur.

The HOME channel dominated the total energy consumption structure (Table 22). Under the baseline scenario, it accounted for approximately 92% of total energy consumption. The APM channel represented approximately 7,5-8,1%, while the contribution of PUDO was marginal owing to the assumed distribution of demand among the delivery channels. It should be noted that the actual demand structure may differ. The values adopted in the model were derived from a 2024 report published by the Office of Electronic Communications [11], which was based on data collected in preceding years. From a system-level perspective, this indicates that changes in the relative shares of delivery channels may substantially affect the overall energy balance of the system, even when the unit energy-consumption parameters of the vehicles remain unchanged.

Table 22. Share of delivery channels in total energy consumption

Delivery channel	Min	Avg	Max
HOME	approx. 91,7%	approx. 92,0%	approx. 92,3%
PUDO	approx. 0,16%	approx. 0,15%	approx. 0,14%
APM	approx. 8,1%	approx. 7,9%	approx. 7,5%

The sensitivity analysis identified three groups of parameters as particularly important: parcel dwell time in a compartment, the rate at which available compartments are replenished, and APM network density. An increase in the average parcel dwell time resulted in higher system capacity utilisation. Under the average-demand scenario, utilisation increased from approximately 0,18 at a dwell time of 0,2 days to approximately 0,57 at the baseline value of 0,625 days, and approached the system capacity limit when the dwell time exceeded approximately 1,1 days. Under the maximum-demand scenario, the system was more sensitive: capacity utilisation was already substantially higher at the baseline value, and any further increase in parcel collection time rapidly led to system saturation.

The second important parameter was the rate at which available compartments were replenished. The results indicate that the physical availability of compartments alone is insufficient unless it is accompanied by an efficient organisation of courier operations. Less frequent servicing of APMs reduces the effective capacity of the system and may lead to parcel redirection or overflow to PUDO points. This finding is operationally significant because it demonstrates that the expansion of point-based infrastructure should be analysed jointly with servicing frequency and the organisation of courier routes.

The third parameter was the number of APMs. Increasing the number of machines reduces the distance between recipients and the nearest APM and decreases the share of car-based collection trips. For a network of 50 APMs, the share of car journeys was estimated at approximately

0,135, while the distance of a dedicated car journey was approximately 1,71 km. For 162 APMs, the corresponding values were approximately 0,065 and 0,736 km, whereas for 400 APMs they decreased to approximately 0,039 and 0,386 km. At the same time, each additional APM generates a fixed component of infrastructure energy consumption. Consequently, the optimal network density cannot be determined solely by minimising recipient travel distance, but must reflect the balance between improved accessibility, reduced car travel, and increased infrastructure energy consumption.

These findings are consistent with the earlier analysis of travel induced by parcel collection from APMs in GZM. That study demonstrated that pedestrian accessibility is a key condition for limiting additional car traffic generated by recipients. In urban areas characterised by a high density of APMs, most residents are located within an acceptable walking time, and the effect of parcel collection on car traffic is therefore limited. In areas with lower development density and fewer APMs, even a relatively small number of car-based collection trips may adversely affect the energy balance of the OOH channel.

The SD model extends this relationship by demonstrating that the number of APMs affects not only recipient travel distance, but also the share of car journeys, recipient energy consumption, and the overall energy balance of the APM channel. Table 23 summarises selected modifications introduced into the SD model during the experimental stage and the resulting system behaviour.

Table 23. Synthesised interpretation of selected scenario results

Scenario variable	Direction of impact	Interpretation
Increase in demand	Increase in total energy consumption and decrease in APM energy consumption per parcel	Economies of scale improve the unit energy efficiency of the APM channel until the system approaches its capacity limit
Longer parcel collection time	Increase in compartment occupancy	Parcel turnover is critical to the effective capacity of the system
Less frequent APM servicing	Decrease in effective system capacity	The number of compartments must be considered jointly with courier servicing frequency
Increase in the number of APMs	Reduction in recipient travel distance and the share of car-based journeys	Accessibility improves, but infrastructure energy consumption increases
Higher share of trip chaining	Reduction in additional recipient energy consumption	Recipient behaviour strongly influences the net energy balance
Fleet electrification	Reduction in local emissions and change in the structure of energy consumption	The resulting effect depends on both the courier fleet and recipients' vehicles

In addition, multi-factor scenarios were developed to examine pessimistic and optimistic system configurations. The pessimistic scenario combined less favourable recipient behaviour, a higher share of car-based journeys, longer parcel dwell times in APM compartments, higher failed-delivery rates, and the continued use of an internal combustion engine fleet. The optimistic scenario assumed greater APM accessibility, a higher share of trip chaining, shorter parcel collection times, a lower proportion of car-based journeys, and fleet electrification. These scenarios demonstrate that the energy performance of the APM channel, as well as that of the delivery system as a whole, is not determined by a single parameter. Rather, it results from the combined effects of infrastructure provision, recipient behaviour, service organisation, and vehicle technology.

It should be emphasised that this component of the research is exploratory and pilot in nature. The SD model integrates data and assumptions derived from multiple sources, including simulation results, spatial analyses, literature-based parameters, and expert assumptions. Consequently, the results should be interpreted primarily as indications of general tendencies and as a means of examining how selected factors influence the behaviour of the urban logistics system. They should not be regarded as definitive quantitative estimates for a specific city, logistics operator, or delivery network.

A rigorous quantitative assessment would require further detailed research based on a precisely defined case-study area, calibrated operational data, and the empirical validation of behavioural and infrastructure-related parameters. Such detailed calibration was not the principal objective of the E-Laas project. Within the project, the role of System Dynamics was instead to support a system-level understanding of feedback relationships, sensitivity effects, and policy-relevant mechanisms in urban logistics.

8.4. Contribution to D2.3 and relation to other modelling streams

The SD layer complements macroscopic modelling, microsimulation, and KPI scaling within D2.3. Its principal value lies in its capacity to represent urban logistics as a dynamic system in which energy performance results from interactions among demand, infrastructure, recipient behaviour, delivery organisation, and fleet technology. In relation to the preceding stages of the research, the SD model performs a different function from both the macroscopic model and the KPI scaling procedure. The macroscopic model enables the spatial distribution of traffic, energy consumption, and emissions to be assessed at the metropolitan scale. KPI scaling allows detailed microsimulation results to be transferred to TAZs exhibiting similar characteristics. System Dynamics, by contrast, supports the analysis of long-term mechanisms, including increasing infrastructure utilisation, the effects of delayed parcel collection, capacity constraints, parcel redirection, shifts between delivery channels, and the influence of recipient behaviour on the energy balance.

An important component of this research stream is the extension of the earlier analysis of travel induced by parcel collection from APMs. Publication [13] provided a method for assessing the spatial accessibility of APMs and estimating the additional car journeys undertaken by recipients. The SD model presented in [17] incorporates this logic into a broader dynamic system in which recipient mobility is linked to the number of APMs, network density, parcel turnover, capacity utilisation, parcel redirection, and energy consumption. Consequently, the behavioural component is not treated as an external addition to the model, but as one of the mechanisms that jointly determine the energy balance of last-mile delivery.

The principal outcome of this component of the research is the development of an approach that enables the conditions under which multimodal, consolidation-oriented, and related solutions can genuinely improve the energy efficiency of last-mile delivery to be assessed. The findings indicate that the mere provision of additional infrastructure does not guarantee a favourable energy balance. The key factors include an appropriate network density, rapid parcel turnover and efficient servicing, a low share of dedicated car journeys, and a high proportion of collections undertaken on foot or as part of other activities.

Such solutions should therefore be analysed not only from the perspective of logistics infrastructure, but as components of a broader system encompassing user behaviour, delivery operations, and urban policy conditions. From an urban policy perspective, the SD model can support the assessment of scenarios involving the expansion of collection-point networks, fleet electrification, improvements in the spatial accessibility of logistics infrastructure, reductions in dedicated car journeys, and more efficient organisation of courier services. The results of this research stream provide a bridge between technical and operational modelling and the subsequent interpretation undertaken within Milestone M2, where greater emphasis will be placed on the implications of the findings for the formulation of Sustainable Urban Logistics Policies.

9. Synthesis of modelling results and contribution to WP2

9.1. Complementary research supporting the modelling framework

In addition to the four principal modelling streams presented in Chapters 5-8, the E-Laas project also included supplementary research activities that complement the modelling framework developed within D2.3. These activities do not constitute separate core modelling layers comparable to macroscopic modelling, microsimulation, KPI scaling, or System Dynamics. Instead, they strengthen the methodological foundation of the project. They concern primarily fleet-related decision-making, delivery planning, risk assessment, the prediction of energy consumption by electric vehicles, the energy intensity of transshipment infrastructure, and concepts for multi-tier parcel distribution.

The relevance of these studies lies in demonstrating the broader applicability of simulation, optimisation, and decision-support methods to the analysis of energy-efficient urban logistics. In particular, they make it possible to relate energy and emission assessment not only to vehicle movements within the urban transport network, but also to fleet selection, route organisation, terminal operations, operational risk, and the design of new distribution architectures.

The first group of complementary studies concerns fleet selection and the environmental consequences of operational decisions. The study on fleet vehicle selection examined how vehicle and driver assignment may be assessed not only through total cost of ownership, but also through emissions and external costs. The model was implemented in the FlexSim environment and combined simulation, optimization and additional emission assessment, including the use of COPERT-based indicators. This work is valuable for D2.3 because it provided an early methodological basis for linking operational vehicle decisions with environmental assessment and showed that fleet structure can significantly affect the environmental profile of transport operations.

Table 24. Complementary research supporting the D2.3 modelling framework

Complementary research area	Main role	Contribution
Fleet selection and pollutant emissions [21]	Assessment of fleet decisions from the perspective of economic and environmental criteria	Shows how simulation, optimization and emission assessment can support vehicle selection and fleet-structure decisions
Urban delivery planning with environmental criteria [7]	Multi-criteria assessment of urban delivery variants	Supports the evaluation of delivery plans with respect to cost, time and environmental exposure
Risk-aware vehicle-task allocation [2]	Inclusion of safety and reliability aspects in operational planning	Extends the modelling perspective beyond energy and emissions by considering route-related operational risk
Predictive modelling of EV energy expenditure [3]	Estimation of energy demand of electric delivery vehicles	Provides methodological support for energy-aware routing, microsimulation and EV operation modelling
Intermodal terminal energy consumption [5]	Assessment of energy use in handling and terminal operations	Extends the energy perspective to logistics infrastructure and intermodal hubs
Multi-level parcel distribution architecture [4]	Conceptual assessment of rail, BDF, microhubs and zero-emission last-mile integration	Broadens the E-Laas perspective from urban last-mile modelling to national-urban distribution architecture

A related contribution is the work on delivery planning in urban areas with environmental aspects. This study proposed a multi-criteria decision-support approach for planning deliveries in an urban transport network. The analysed criteria included the cost, time and amount of ecosystem exposure to harmful compounds, while the method combined spatial data processing, routing and emission-factor-based assessment. In relation to D2.3, this work supports the interpretation of urban delivery variants as decision alternatives that can be compared using both operational and environmental criteria.

Another complementary direction concerns risk-aware operational planning. The study on risk management in the allocation of vehicles to tasks developed a decision model and heuristic procedure for assigning vehicles to transport tasks while minimizing the probability of dangerous events on routes. The model includes classical constraints of vehicle-task assignment, such as time windows and vehicle capacity, but additionally introduces an acceptable risk constraint and a risk-minimizing objective function. This research broadens the WP2 perspective by showing that practical planning of urban and regional logistics should consider not only energy, emissions and cost, but also safety, reliability and the probability of disruptions in transport operations.

The predictive modelling of energy expenditure of electric delivery vehicles is directly connected with the energy-oriented logic of E-Laas. The study developed regression and neural-network models for estimating the energy consumption of electric delivery vehicles operating in urban service enterprises. The explanatory variables included route-segment length, vehicle weight with load, departure time from the base, number of loading and unloading points, number of stops, terrain slope and wind speed. This work provides useful methodological background for energy-aware modelling of electric delivery operations, especially where direct measurement of speed and acceleration profiles is difficult or unavailable.

The energy assessment perspective was also extended to logistics infrastructure. The study on overhead crane energy consumption in intermodal terminals analysed how container location, rehandling operations and train-loading strategies influence the energy use of handling equipment. The model was developed in FlexSim and focused on the energy consumption of gantry crane movements during the train loading process. This work is relevant in the context of D2.3 because it shows that energy use in urban logistics is not limited to vehicles and last-mile routes, but also includes the operation of terminals, hubs and transshipment infrastructure. It also provided an early research basis for considering the use of intermodal transport in last-mile delivery systems. This perspective was further developed in the conceptual work on a multi-level parcel distribution system based on rail transport, BDF swap bodies and zero-emission last-mile logistics, which provides a broader system architecture for parcel flows. The proposed concept links a central logistics node, interregional rail redistribution, mobile microhubs and zero-emission urban delivery. Its role in relation to D2.3 is mainly strategic and conceptual. It extends the analysis from selected urban delivery processes to a multi-level distribution structure connecting national, regional and urban logistics layers. This direction is consistent with the E-Laas objective of analysing scalable and energy-oriented logistics solutions.

These studies strengthen the modelling framework documented in D2.3. They confirm that the assessment of energy-optimal urban logistics requires a broader analytical perspective, covering vehicle technologies, delivery planning, fleet decisions, infrastructure operations, risk, user behaviour and system architecture.

9.2. Synthesis across modelling levels

The work documented in D2.3 constitutes a coherent set of modelling approaches developed for the energy assessment of urban distribution systems. Each modelling level performs a distinct function within the WP2 research workflow. These levels are summarised in Table 25. Macroscopic modelling enables the magnitude and spatial distribution of freight transport impacts to be assessed. Microsimulation supports the detailed analysis of last-mile delivery processes. KPI scaling integrates the microscopic and macroscopic levels by enabling the results of detailed simulations to be transferred to a broader spatial scale. SD structures the dynamic relationships and feedback loops between demand, infrastructure, user behaviour, and energy consumption.

Table 25. Synthesis of modelling levels in D2.3

Modelling level	Main role in D2.3	Main outputs	Related research
Macro-level modelling	metropolitan-scale assessment of urban freight transport	energy consumption, emissions, external costs, spatial burden, scenario comparison	macroscopic GZM-based environmental impact assessment
Micro-level modelling	last-mile process assessment	operational KPI, delivery time, distance, vehicle work, energy and CO_2 indicators	FlexSim-based last-mile delivery modelling
Macro-micro KPI scaling	transfer of simulation results from reference zones to similar TAZ	TAZ clusters, scaling functions, estimated KPI for larger areas, validation errors	TAZ similarity, clustering and KPI scaling studies
System Dynamics	systemic interpretation of feedback relations	causal structure, demand-capacity relations, infrastructure utilisation, behavioural effects, policy interface	APM-based System Dynamics model and stakeholder-oriented SULP interpretation

This framework makes it possible to analyse urban logistics as a multilevel system. At the operational level, delivery processes, routes, vehicles, and service times are assessed. At the urban level, the spatial distribution of vehicle activity, energy consumption, and emissions is examined. At the integrative level, the analysis focuses on how locally obtained results can be transferred to zones exhibiting similar characteristics. At the system level, the research addresses relationships that evolve over time and influence the long-term energy efficiency of urban logistics.

The modelling work focused on selected representative urban logistics flows that allowed the project team to test the applicability of energy-based assessment at different levels of spatial and operational detail. The selected research streams covered courier B2C deliveries, last-mile delivery processes, parcel lockers and out-of-home delivery channels, vehicle and fleet-related decisions, TAZ-based spatial differentiation, and the environmental impact of freight transport in the GZM and other cases.

9.3. General findings

The modelling work carried out in WP2 confirms that urban logistics requires simultaneous operational and spatial assessment. Detailed last-mile processes cannot be fully interpreted without considering the urban structure, transport network, density of demand and accessibility of logistics infrastructure. At the same time, macro-level assessment alone is not sufficient to explain the operational mechanisms behind energy use, delivery time, route length or service efficiency. The combination of macro and micro approaches is therefore necessary to obtain a more complete picture of energy-optimal urban logistics.

Energy and emission indicators depend strongly on the level of aggregation. At the macro level, the main value lies in identifying spatial burdens, road classes, traffic flows and areas with high environmental impact. At the micro level, the key information concerns delivery routes, vehicle operations, stop density, service time and process organisation. At the system level, the same indicators must be interpreted in relation to feedback mechanisms, infrastructure capacity, user behaviour and changes in demand over time.

Different delivery technologies and channels have different operational and energy profiles. Direct home delivery, parcel lockers, PUDO points, electric vehicles, drones and conventional delivery vehicles cannot be compared only by one indicator. Each solution changes the distribution of work between operator, vehicle, infrastructure and recipient. Parcel lockers may reduce courier mileage through consolidation, but their final energy effect also depends on user trips, walking accessibility, trip chaining, locker utilisation and the energy demand of the infrastructure. Electric vehicles reduce local emissions, but they also shift attention toward energy demand, charging infrastructure and operational scheduling. Micro-level results should not be mechanically transferred to the whole city without assessing the similarity of areas. Last-mile KPI are sensitive to local features such as population density, road network density, land-use structure, travel time, number of delivery points and spatial distribution of demand. The use of TAZ similarity and clustering allows simulation results to be transferred in a more controlled way, by linking reference areas with other TAZs that share similar characteristics. TAZ-based KPI scaling reduces the analytical burden of urban logistics simulation. Instead of building detailed microsimulation models for all TAZs, representative zones can be selected, simulated and used as a basis for estimating KPI in similar areas. This approach increases the scalability of the research workflow and supports the practical use of detailed simulation results in larger urban or metropolitan contexts. System Dynamics provides a useful layer for organising the relationships between modelling results and urban logistics policy. It allows the analysis to move beyond isolated model outputs and to consider causal mechanisms such as demand growth, capacity limits, delays, parcel dwell time, infrastructure utilisation, recipient mobility and fleet electrification. In this sense, SD supports the transition from technical modelling in D2.3 to policy-oriented interpretation in M2.

Overall, the results confirm that energy-optimal urban logistics should be treated as a multi-level problem. It includes operational efficiency, spatial structure, user behaviour, infrastructure capacity, fleet technology and policy context. None of these dimensions is sufficient on its own. The main contribution of WP2 is therefore an integrated modelling framework that combines several complementary methods for assessing energy use and environmental effects in urban distribution systems.

10. Conclusions

The work documented in Deliverable D2.3 constitutes a coherent set of modelling and simulation approaches developed to support the energy assessment of urban logistics flows. The research combined several complementary approaches addressing different levels of analytical detail: macroscopic, microscopic, integrative, and system-wide.

The research conducted within WP2 was primarily fundamental and methodological in nature. Its objective was to develop, test, and systematise research approaches capable of analysing the energy intensity of urban logistics at different levels of detail. The models and results presented in D2.3 draw on data obtained from multiple sources, including transport models, spatial datasets, simulation experiments, scientific literature, scenario assumptions, and empirical data used in selected detailed studies. Consequently, the results should be interpreted primarily as a basis for identifying mechanisms, trends, and system-level relationships, rather than as definitive quantitative estimates for a specific city, logistics operator, or distribution network.

This interpretation is consistent with the objectives of the E-Laas project and the scope of WP2. The purpose of the research was not to develop an implementation-ready operational model for a single, precisely defined case, but rather to establish a transferable analytical framework for assessing and comparing alternative urban logistics solutions from the perspectives of energy consumption, emissions, process organisation, and user behaviour, as well as for identifying general trends, relationships, and regularities. A rigorous quantitative assessment of a specific system would require further detailed research based on comprehensive local data, operator datasets, field measurements, and the empirical validation of behavioural and infrastructure-related parameters.

The work undertaken within D2.3 demonstrates that energy-efficient urban logistics should be analysed as a multilevel problem. Energy consumption and emissions depend not only on vehicle technology, but also on demand density, the spatial structure of the city, the organisation of delivery channels, the availability of logistics infrastructure, recipient behaviour, and the operational decisions of logistics operators. No single component is sufficient to assess the overall performance of the system. Their integration, however, provides a broader perspective and enables a multidimensional assessment.

Deliverable D2.3 provides the modelling and analytical foundation for the subsequent interpretation of the results at the milestone level, particularly within Milestone M2. D2.3 documents the models, indicators, simulation logic, selected results, and interrelationships between the methods applied, while also providing a synthesis of the principal findings. Milestone M2 will focus on interpreting these findings from the perspective of Sustainable Urban Logistics Policies, implementation barriers, and potential measures supporting energy-efficient urban freight distribution.

Detailed numerical results, complete experimental configurations, validation procedures, and extended scenario analyses are documented in the associated research outputs. In Deliverable D2.3, these findings are synthesised to the extent necessary to document WUT's contribution to the implementation of the task, demonstrate the coherence of the developed approach, and indicate how the models and research tools developed within WP2 support the overall E-Laas project workflow.

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