# FeDerated nEtwork of pLatforms for Passenger and freigHt Intermodality

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# D.4.1: Environmental, social, financial parameters for multimodal optimisation report

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# Executive Summary

Deliverable D4.1: Environmental, Social and Financial Parameters for Multimodal Optimisation provides a comprehensive analysis of the factors that are taken into account in optimisation problems in the field of multimodal transport, with a special focus on the integration of passenger and freight systems. The incorporation of the environmental, social and financial dimension of sustainability through the use of different optimisation parameters is explored. Following that, the key identified parameters are classified and prioritised, before investigating how the innovations that are being developed in the context of DELPHI can contribute to addressing different gaps and challenges that derived from the literature. The selected environmental, social and financial parameters will be exploited by the decision support system that will be developed in subsequent DELPHI tasks.

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# Abbreviations & Acronyms

| Abbreviation / acronym | Description |
|---|---|
| AI | Artificial Intelligence |
| CO | Carbon monoxide |
| CO2 | Carbon dioxide |
| D1.1 | Deliverable number 1 belonging to WP 1 |
| EC | European Commission |
| GAP | Generalized Assignment Problem |
| GRASP | Greedy Randomized Adaptive Search Procedure |
| ILP | Integer Linear Programming |
| IPFT | Integrated Passenger and Freight Transport |
| IPFT | Integrated Passenger and Freight Transport |
| KPI | Key Performance Indicator |
| LAP | Location-Allocation Problem |
| MILP | Mixed Integer Linear Programming |
| MIP | Mixed Integer Programming |
| ML | Machine Learning |
| O3 | Ozone |
| PBL | Planetary Boundary Layer |
| PMx | Particulate Matter |
| PT | Public Transport |

| Abbreviation / acronym | Description |
|---|---|
| TSP | Travelling Salesman Problem |
| UAM | Urban Air Mobility |
| UAVs | Unmanned Aerial Vehicles |
| UFP | Ultrafine Particulate matter |
| VKT | Vehicle Kilometers Travelled |
| VOCs | Volatile Organic Compounds |
| VRP | Vehicle Routing Problem |
| VRUs | Vulnerable Road Users |
| WP | Work Package |

# 1. Introduction

## 1.1 Objective of the report

This deliverable report is the outcome of DELPHI T4.1, and its main objective is to define the key environmental, social, and financial parameters that can serve as critical factors for the facilitation of multimodal optimisation algorithms that will be developed in the context of the project. These parameters form the foundation for implementing a multi-criteria optimisation approach, ensuring that the models and the decision support system that will be developed in subsequent tasks—T4.2, T4.3, and T4.4—are robust and capable of supporting comprehensive multi-modal transportation planning decisions.

## 1.2 Intended readership

This report is intended to serve a broad audience, both within and beyond the DELPHI consortium.

Within the consortium, the primary readership includes all project partners, but mainly teams directly involved in the development and application of the multi-modal optimisation algorithms of the project. Specifically, partners working on WP4 (Tasks T4.2, T4.3, and T4.4) will use the findings and parameters defined here as a foundation for their work.

Beyond the consortium, this deliverable is also of interest to a wide range of external stakeholders, such as professionals and organizations in the transport industry, academic and research institutions, end users and beneficiaries, policy makers and regulators, technology developers and environmental organizations.

## 1.3 Document Structure

This deliverable is organised in the following 6 main sections, each serving a specific purpose in defining key parameters and their role in the optimisation processes:

**1. Introduction:** Outlines the purpose of the deliverable, its relevance to the project, and the intended readership.

**2. Methodology:** Presents the methodological approach followed to reach its objectives.

**3. Literature review:** Provides an overview of the current state-of-the-art in optimisation methods and practices, focusing on the three pillars of sustainability: environmental, social and financial. Gaps and challenges in existing approaches are identified, creating a basis for the project's innovations.

**4. Combined freight and passenger transport enabling factors:** In this section, the factors that facilitate combined passenger and freight transport optimisation are

investigated. Emphasis is put on strategic and operational integration factors, sensor data correlation, emissions estimation, and the use of AI/ML-powered decision techniques.

**5. DELPHI innovations:** This section describes which of the identified parameters and enabling factors will be applied to the project's innovative optimisation processes, and why, focusing on their role in advancing the DELPHI system's capabilities.

**6. Conclusions:** The document concludes with a summary of the findings, highlighting their importance to the project, as well as to a wider audience.

# 2. Methodology

The main focus of this deliverable report is to identify and interpret parameters that influence multimodal optimisation, considering all three pillars of sustainability: environmental, social, and financial. Initially, a comprehensive and thorough literature review of the current methods used in multimodal transport optimisation is performed, and gaps and challenges that need to be addressed are identified. This process contributes to realizing what is working well, what is still missing and where value could be added through innovation. Alongside this, the key factors that can enable better integration of combined passenger and freight transportation are explored, highlighting the role of multi-modal sensor correlation, emissions and noise estimation, as well as on causal reasoning techniques and AI/ML-powered decision support with predictive capabilities.

To ensure a clear and practical focus, a step-by-step approach is employed to analyse the aforementioned factors. Initially, they are documented comprehensively; a classification and prioritization based on their importance and relevance follows. Finally, this broad list is refined into a focused set of factors that will directly contribute to the DELPHI optimisations. All the above are then used to outline the DELPHI innovations, with special attention given to the integration of freight and passenger transportation optimisation. This systematic process ensures that the project is built on a robust foundation of evidence and insight.

# 3. Literature review

## 3.1 Optimisation in multi-modal transportation: state-of-the-art

In the field of transportation, there is a constantly growing volume of literature but also a wide pool of different optimisation methods and tools met in practice, aiming at addressing optimisation problems of different type, such as the travelling salesman problem (TSP)[1] or the vehicle routing problem (VRP). As the focus of this report, and of the DELPHI project in general, is multimodal transportation and in particular the integration of freight and passenger components, optimisation studies and use cases that refer to unimodal transportation, either freight or passenger, are considered out of scope and are not included in this state-of-the-art analysis.

Focusing on freight transportation, a recent comprehensive literature review by Archetti et al. (2022)[2] presents the state-of-the-art in multimodal optimisation for different combinations of modes. This review entails a classification of existing relevant papers in 8 categories, based on the type of optimisation decision that needs to be taken in each case. According to it, optimisation problems in this field, that are either tactical/strategic or operational, can include finding the optimal: location(s), network design, scheduling (or schedule recovery after a disruptive event), combination of transportation services, fleet renewal, resource allocation or routing. Some optimisation problems are common for most modes, while there are others that are often or always associated with specific modalities (e.g. vessel schedule recovery).

The integration of passenger and freight transport is a topic that has gained increasing interest by the research community (for a comprehensive literature review see Cavallaro and Nocera, 2022[3]), especially for the first/last mile legs of a trip (e.g. see Bruzzone et al., 2021[4]; Arvidsson et al., 2016[5]). Integrating freight into urban public transportation can contribute to eliminating the negative effects of city logistics, by reducing $CO_2$ emissions and congestion in urban areas (Elbert and Rentschler, 2022[6]).

An important strategic decision to take when transit services are considered for the movement of freight is which lines and stops of the public transport network of a city should be part of the plan. To assist decision-making in this direction, Donne et al.

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[1] Travelling Salesman Problem: "The problem of finding the shortest path that passes through a given set of points once and only once, as when a travelling salesman needs to visit a number of specified cities exactly once, using the shortest possible route." Source: https://www.oxfordreference.com/display/10.1093/acref/9780199657681.001.0001/acref-9780199657681-e-8560

[2] https://doi.org/10.1016/j.ejor.2021.07.031

[3] https://doi.org/10.1016/j.rtbm.2021.100718

[4] https://doi.org/10.1016/j.tranpol.2020.10.009

[5] https://doi.org/10.2148/benv.42.4.523

[6] https://doi.org/10.1016/j.rtbm.2021.100679

(2023)[7], proposed mixed integer programming (MIP) modelling, designed a MIP heuristic[8] using a column generation approach and highlighted that the accuracy of their approach has the potential to increase by the use of stochastic optimisation to account for varying customer demand and uncertainty. On the planning phase, another key decision to be taken when the bus network is considered, is how many buses would need to undergo adaptations in order to be able to accommodate freight transportation. Machado et al. (2023)[9] suggested a way to address this fleet optimisation problem through integer linear programming (ILP) modelling and heuristic algorithms based on the greedy randomized adaptive search procedure (GRASP). In this case, stochastic parameters to account for uncertainty were incorporated in their proposed methodology.

In some countries with established urban railway systems, such as France, Germany and the Netherlands, there are cases where freight is also transported through it (Ozturk and Patrick, 2018)[10]. Based on two real-world examples in Paris, Ozturk and Patrick (2018), developed a heuristic optimisation framework that comprises two mixed integer linear models for employing existing urban/suburban rail infrastructure for the transportation of dedicated freight carriers; one of the models focuses on minimizing the number of required trains.

The use of unmanned aerial vehicles (UAVs) - or drones, as they are widely known - in combination with other modes to optimize parcel deliveries in urban areas has been lately the focus of different studies, and it is already used in practice by companies such as Amazon and DHL. A number of the related studies, consider this an extension of the TSP, for instance Murray and Chu (2015)[11] examine, by proposing a new heuristic framework, what they define as the flying sidekick travelling salesman problem: a group of customers, each of whom should receive a parcel only one time, by either a human - operated truck or a drone coordinated with a truck. Wang et al. (2021)[12], develop a two-phase heuristic algorithm to address a multiple TSP intertwined with a location-allocation problem (LAP) for a last-mile parcel delivery system that combines vans, trucks and drones.

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[7] https://doi.org/10.1016/j.trb.2023.01.004

[8] "Heuristics is an approach to problem-solving in which the objective is to produce a working solution within a reasonable time frame. Instead of looking for a perfect solution, heuristic strategies look for a quick solution that falls within an acceptable range of accuracy […] Because a heuristic approach emphasizes speed over accuracy, it is often combined with optimisation algorithms to improve results." Source: Rouse (2023) (https://www.techopedia.com/definition/5436/heuristic).

[9] https://doi.org/10.1016/j.tra.2023.103645

[10] https://doi.org/10.1016/j.ejor.2017.12.010

[11] https://doi.org/10.1016/j.trc.2015.03.005

[12] https://www.mdpi.com/2079-9292/10/20/2510

Another study that focuses on drones and trucks in tandem delivery network combines (meta)heuristics with mathematical programming, and develops a matheuristic[13] algorithm (Chu et al., 2024)[14]. This study highlights the element of drone safety and collision avoidance, by integrating drone trajectories into the route planning problem. Liu et al. (2024)[15] have investigated the joint truck-drone routing optimisation for last-mile deliveries, using an improved genetic algorithm that can take into account real-time customer demand.

## 3.2 Environmental pillar

Despite extensive research on the noxious effects of traffic-related pollutants such as carbon monoxide (CO), particulate matter (PMx), volatile organic compounds (VOCs), and ozone (O3) on human health, there is comparatively little efforts to incorporate polluted environmental conditions into routing optimisation schemes. Exposure to traffic-related pollutants can lead to several health issues including damage to the respiratory system, cognitive system, nervous system, and even increased mortality. These pollutants, often concentrated in urban areas with high traffic density, pose significant health risks, particularly to vulnerable populations such as children and active commuters.

Several studies have aimed to quantify children's exposure to traffic pollutants. An et al. (2022)[16] conducted a comparative study on exposure to particulate matter ($PM_{2.5}$ and $PM_{10}$) along two distinct walking routes, a high-traffic and a low-traffic route, to a primary school in China. Their analysis found that students traveling along the low-traffic route breathed on average 16.3% less amount of PM2.5 per year. The study underscores the importance of avoiding main roads with signalized traffic intersections as particularly high concentrations of particulate matter occur there due to stop-and-go behavior of the vehicles. Similarly, Elford and Adams (2019)[17] examined exposure to ultrafine particulate matter (UFP) during school commutes, focusing on active mobility and terrain-related ventilation rates. Their approach demonstrated how factors related to physical exertion, such as terrain slope and walking speed, increase respiratory doses consequently extending UFP exposure. Furthermore, Mölter and Lindley (2015)[18] analyzed $NO_2$ and $PM_{10}$ exposure for primary school children in Manchester, UK. The results showed that low pollution routes drastically reduce exposure with minimal increased travel time, supporting the need for routing frameworks which include

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[13] A matheuristic is "the hybridization of mathematical programming with metaheuristics" (Fischetti and Fischetti, 2018).
[14] https://doi.org/10.1016/j.cie.2024.110000
[15] https://doi.org/10.1080/23249935.2024.2392611
[16] https://pubmed.ncbi.nlm.nih.gov/35091940/
[17] https://www.sciencedirect.com/science/article/pii/S0013935119304712
[18] https://www.sciencedirect.com/science/article/pii/S0048969715301765

environmental factors. Similar results are reported in Bigazzi et al. (2016)[19] for urban cyclists. The paper indicates that not only low-traffic routes are often less polluted, but in the case of cyclists, they also align with their preferences for safer paths.

Moreover, various papers claim that population exposure for urban commuters is often miscalculated. In Li et al. (2023)[20], the first and last mile of urban commutes, often involving active transportation modes like walking or cycling, is analyzed. The study reveals that the differences in exposure to pollutants between lowest-dose routes and fastest routes are below 1% due to the close relationship between accumulated exposure and exposure time. However, behavior-based routes are usually distinct to those routes and the average exposure doses of PM2.5 and NO2 is between 8% and 13% higher approximately, therefore usually underestimating commuter exposure. Park and Kwan (2016)[21] concluded that spatiotemporal variability of air pollution and human daily movement patterns are to be accounted for accurate exposure calculation, considering that models using residential and daily pollution data tended to overestimate the actual exposure.

Examples of optimisation, including environmental factors, come from freight transportation research. Zhang et al. (2013)[22] developed a multimodal network optimisation model incorporating $CO_2$ emission pricing as a relevant variable influencing terminal use and optimal allocation. By applying this model to the Dutch container terminal network, the study demonstrated including pricing mechanisms, more specifically $CO_2$ pricing, could drive more efficient logistics operations while simultaneously reducing environmental impacts.

### 3.3 Social pillar

While recently there has been an increasing tendency in the literature in attempting to account for all three pillars of sustainability when optimisation techniques are employed, the social viewpoint is still not included in optimisation problems as often as the environmental one (e.g. see Becerra et al., 2023[23]; Messman et al., 2020[24]). It is worth noting that multi-objective optimisation as well as social sustainability index emerged as recurring research topics for the last years, in the field of socially sustainable transport research, according to a bibliometric analysis by Bao et al. (2023)[25]. The researchers highlighted that especially the period between 2015 and 2021 can be called the "rapid development stage", as during these years, a

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[19] https://www.sciencedirect.com/science/article/pii/S2214140515007021
[20] https://www.sciencedirect.com/science/article/pii/S0959652623024022
[21] https://www.sciencedirect.com/science/article/pii/S1353829216304415
[22] https://www.sciencedirect.com/science/article/pii/S0166361512002011
[23] https://doi.org/10.1080/00207543.2023.2197515
[24] https://doi.org/10.1016/j.jclepro.2020.120459
[25] https://doi.org/10.1016/j.tbs.2022.08.012

considerable growth in the number of articles related to sustainable transport under a social perspective took place.

Messman et al. (2020)[26] conducted a literature review on how to assess and integrate social aspects into supply chain optimisation on a strategic level and found that the most frequently used social indicator in the existing literature is the number of new job opportunities created; the authors highlight that in many cases this is the only social factor taken into account. Other social factors that have been identified by the same study are regional economic development and work safety. Another study, by Yang and Song (2020)[27] introduced a regional transportation infrastructure utilization index to integrate the social dimension in their multi-objective optimisation model of sustainable multi-modal transport.

The impact on traffic safety is another parameter that falls under the umbrella of social factors. A multi-objective integer programming model and a hybrid heuristic based on machine learning, for minimizing accident rate, as well as $CO_2$ emissions and logistics costs, is suggested by Aloui et al. (2021)[28] for urban freight trips, considering this way all three pillars of sustainability. Sahnoon et al. (2018)[29] proved that taking into consideration the traffic safety component can affect the overall route selection in vehicle routing problems.

Incorporating the users' perspective into an optimisation framework is another way to integrate the social dimension. For instance, Hohmann et al. (2024)[30], performed multi-objective optimisation of urban air mobility (UAM) networks under a social lens, using Frankfurt, Germany, as a case study, and concluded that doing so can have a major positive impact on social acceptance of UAM. The integration of users' preferences, such as perception of convenience, into ride-sharing problems' optimisation is the subject of work of Dastani et al. (2024)[31], resulting, according to them, in enhanced user satisfaction comparing to models that do not consider those attributes. Yu et al. (2024)[32] incorporated the parameters of driver equity and flexible route consistency into a consistent vehicle routing problem, investigating whether this has added value to the decision-making process. Focusing on optimizing food supply chains in Latin

[26] https://doi.org/10.1016/j.jclepro.2020.120459
[27] https://www.matec-conferences.org/articles/matecconf/pdf/2020/21/matecconf_ictle2020_03001.pdf
[28] https://doi.org/10.1016/j.scs.2021.103331
[29] https://doi.org/10.1007/978-3-319-60441-1_25
[30] https://tuprints.ulb.tu-darmstadt.de/28158/1/Multi-Objective_Optimisation_of_Urban_Air_Transportation_Networks_Under_Social_Considerations.pdf
[31] https://doi.org/10.1038/s41598-024-78469-1
[32] https://doi.org/10.1016/j.cie.2023.109803

America, Granillo-Macías (2021)[33] included factors such as poverty levels, food insecurity and social exclusion in the clustering techniques used for the optimisation.

## 3.4 Financial pillar

In contrast to the environmental and especially the social pillar, which, as mentioned in the previous sections (3.2 and 3.3) have gained increasing interest in the research community especially during the last decades (and was often disregarded in the past, e.g. in supply chain optimisation (Darvish et al., 2019)[34]), the financial pillar is the one with the most extensive existing literature in the field of transportation optimisation, both in passenger and in freight transport. There are many studies that seek how to minimize the total transport costs, which could include direct costs, as well as indirect costs related to the travel time for instance.

Some studies focus on the simultaneous optimisation of different cost-related factors across different transport modes. For instance, the one conducted by Rejeb et al. (2023)[35], uses metaheuristic algorithms to optimise overall transportation cost, travel time and environmental cost (CO2 emissions) considering multimodality in road, rail, air and sea. Similarly, Sitek and Wikarek (2012)[36], who examined supply chain optimisation from the point of view of a multimodal logistics provider, the parameters included in the MILP optimisation model they developed were the production, transport and environmental cost.

Johar et al. (2024)[37], employ cost-related factors, such as production cost, transport time and penalty cost using a genetic algorithm to calculate the optimal supply chain benefits for multimodal transport distribution, within specific time constraints. The integration of autonomous demand-responsive transit into public transit to assist with first/last mile trips is investigated by Narasimhamurthy Sharath et al. (2024)[38], aiming to suggest routes for which user, operator as well as emission costs would be optimized. The authors highlighted that an AI-driven approach could be a potentially interesting future replacement of the fuzzy-logic used in their study.

In optimisation problems that include the use of UAVs in combination with other modes, as presented in section 3.1, the objective can be the optimisation of the total delivery costs (trucks and drones) (e.g. see Wang et al., 2021[39]) or increasing the

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[33] https://doi.org/10.1016/j.seps.2020.100972

[34] https://doi.org/10.1016/j.ijpe.2018.08.020

[35] https://doi.org/10.1007/978-3-031-50036-7_5

[36] https://intapi.sciendo.com/pdf/10.2478/fman-2013-0012

[37]  https://doi.org/10.11113/mjfas.v20n1.3184

[38] https://doi.org/10.1016/j.trip.2024.101289

[39] https://doi.org/10.3390/electronics10202510

delivery speed while limiting cost as well as environmental footprint (e.g. see Murray and Chu, 2015[40]).

## 3.5 Findings and challenges

The literature review showed that various financial, environmental, and social parameters are used in different optimisation studies, in their attempt to find the optimal balance among diverse and often conflicting objectives related to multimodality and the combination of passenger and freight transport. Regarding the environmental dimension, the factor that is most often taken into consideration in the existing literature is the $CO_2$ emissions, while in order to minimize environmental costs, a more holistic approach that looks at other factors such as noise pollution, congestion and climate change would be essential (Ferjani et al., 2024[41]).

Moreover, handling trade-offs between cost minimization and environmental/social objectives is an important remaining challenge (Darvish et al., 2019[42]; Gružauskas et al., 2018[43]). Using a flexible optimisation framework that can be adapted to local characteristics can be useful for tailored-made solutions in multi-modal transportation optimisation problems (Derpich et al., 2024[44]). Additional challenges with regard to multi-modal transport optimisation can be the impact of dynamic traffic conditions such as congestion or traffic disruptions due to accidents or other unexpected events, delivery constraints especially in complex urban environments and computational challenges due to the large volume of datasets required to increase accuracy and receive high-quality results.[45]

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[40] https://doi.org/10.1016/j.trc.2015.03.005
[41] https://doi.org/10.1016/j.multra.2024.100151
[42] https://doi.org/10.1016/j.ijpe.2018.08.020
[43] https://doi.org/10.1016/j.jclepro.2018.02.302
[44] https://doi.org/10.3390/jmse12060976
[45] https://www.linkedin.com/pulse/navigating-roadblocks-overcoming-route-optimisation-sam-armani-phd-gbezc/

# 4. Combined freight and passenger transport enabling factors

## 4.1 Integrated freight and passenger transportation optimisation

### 4.1.1 Preliminary list of factors

The integration of passenger and freight transportation services into the same transportation system, often referred to as "Integrated Passenger and Freight Transport" (IPFT), constitutes a branch of transportation that has received considerable research attention but minimal field application, due to the difficulties it entails. A literature review on IPTF systems is provided by Cavallaro and Nocera (2022)[46], and by Elbert and Rentschler (2022)[47] with a focus specifically on urban areas. Furthermore, the state-of-the-art analysis and the approaches of Lu et al. (2022)[48] and Bruzzone et al. (2023)[49] provide more insights concerning the optimisation of IPTF systems.

### 4.1.2 Classification/prioritization

Designing and implementing such a system commonly involves regulating and/or considering several strategic and operational factors that affect the cost and effectiveness of these systems, the most common of which can be summarized and classified, based on the aforementioned references, in the following way:

- Strategic Factors related to spatial planning and transport infrastructure design/re-organization
  - Space re-organization and accessibility guarantee
  - Minimization of conflicts between flows of different users/vehicles
  - Urban consolidation facilities outside of main urban space
  - Shared road infrastructure (multi-use lanes, night parcel deliveries, shared bus/lorry lanes)
  - Shared public transport services (buses, subway, tramway, car sharing carrying passengers and cargo)
    - Number of lines/routes and vehicles with parcels
    - Location of depots at PT stations
    - Crowdshipping possibility
  - Shared taxis (pax and cargo)

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[46] https://www.sciencedirect.com/science/article/pii/S2210539521001012
[47] https://www.sciencedirect.com/science/article/pii/S2210539521000626#bb0025
[48] https://www.sciencedirect.com/science/article/pii/S1366554521003045
[49] https://www.sciencedirect.com/science/article/pii/S2590198223002051

- o Shared consolidation facilities (hubs) - location & operation of passenger and parcel depots (e.g. delivery bays, lockers in car parks or underground stations, delivery stations in car parks)

- Tactical and operational organization factors (shared approach to improve performance) for optimally solving the respective vehicle routing problem
  - o Scale of transport distance-wise (long-haul / short-haul)
  - o Territorial context (urban, sub-urban, rural areas)
  - o Type of vehicle (conventional car, taxi, bus, van, truck)
  - o Type of driver and fuel technology of considered vehicles
    - Conventional gas vehicles (cars/trucks)
    - Electric vehicles
    - Human driven cars or autonomous cars
    - Conventional or electric bikes / electric scooters
    - Manually flown or automated UAVs (drones)
  - o Vehicle capacity for passengers (e.g. Uber, Lyft ride sharing) and parcels (available storage volume)
  - o Operational cost per vehicle type
  - o Specific factors per vehicle type. E.g. for electric vehicles:
    - Electrical energy consumption
    - Battery capacity (max distance covered)
    - Charging requirements (charging location & duration)
  - o Type and size of available fleet (mixed, all-electric, all-gasoline)
  - o Type of trip requests (in-advance or current time)
  - o Trip demand variations throughout the day (passenger demand in peaks vs. parcels demand more uniform)
  - o Time windows for parcel deliveries / trip duration and expected arrival windows for passengers
  - o In-vehicle spatial and temporal allocation between passengers and freight (security factors, where are passengers vs. freight, transport at the same or different times)
  - o Assignment of parcels and passengers to vehicles and hubs and respective path/route decision
  - o Pricing of routes for passengers/parcels to maximize profits from the side of transportation operators

- Social and environmental factors
  - o Sustainability, public health and environmental protection
    - Global energy consumption
    - Atmospheric emissions (e.g. greenhouse gas emissions)
    - Hazardous airborne particles

- Noise emissions
  - o Safety topics
    - Transport Regulations (e.g. common use of space by passengers and parcels, handling of sensitive/suspicious parcels, hygiene etc.)

Infrastructure maintenance (e.g. rail systems)
  - o Accessibility to various types of users (e.g. remote users, reduced mobility, lower income)
  - o Impact of large freight transportation vehicles (trucks) in urban congestion levels during peak hours

### 4.1.3 List of optimisation factors addressed in DELPHI optimisations

In DELPHI multi-modal optimisation approach for passenger and freight transportation, the following factors have been taken into consideration during the formulation of the problem, either as decision variables or as part of the objective function costs or the problem constraints. More precisely, categorized from the aspect of the partner that is associated with each case, the list of relative factors is as follows:

- Metro:
  - o Locations of hub stations and included metro lines crossing them
  - o Capacity of metro vehicles operating at each line

- Logistics company:
  - o Capacity of trucks
  - o Emissions of trucks
  - o Operating cost of trucks
- Last-mile delivery:
  - o Cost of compensation per delivery
  - o Maximum distance they can spend
  - o Capacity of each KOIKI

- Additional assumptions on:
  - o Maximum number of KOIKI employees
  - o Shift duration of KOIKI employees
  - o Speed of walking/biking of KOIKI employees

### 4.2 Multi-modal sensor correlation, emissions and noise estimation

### 4.2.1 Preliminary list of factors

The increasing need for emissions mitigation strategies has led to the development of methodologies to assess $CO_2$ and noise emissions caused by road traffic in urban

environments. Traditional modelling techniques provide a broader understanding of vehicular emissions, complemented by real-time data collection from advanced sensor systems. These methodologies enable localized analysis, contributing to urban sustainability initiatives.

The DELPHI monitoring system is implemented to collect and analyse multi-modal environmental data during drone flights for the Athens use case. The system utilizes advanced sensors and reliable communication networks to monitor key factors such as $CO_2$ emissions and noise levels, providing valuable insights for project execution.

**System components:**

The multi-modal environmental monitoring system includes four sensor nodes, each equipped with a $CO_2$ sensor (PSCO2) and a microphone (IM69D). These sensor nodes are strategically installed on both sides near the Athen highway toll booth to collect $CO_2$ emissions and noise. The collected data is transmitted from the sensor nodes to a central gateway, where it is logged locally. The gateway then uploads the processed data to the cloud for further analysis.

The key features and components of the system are as follows:

| Gateway*1 | Sensor Node*4 |
|---|---|
| <ul><li>Raspberry Pi 4 Model B based</li><li>863 MHz Sub-GHz</li><li>BLE and WIFI connectivity</li><li>Generic USB drive</li><li>Local data logging</li><li>MQTT connection to cloud</li><li>Touchscreen</li></ul> | <ul><li>Infineon PSoC 6 core</li><li>Sub-GHz communication module</li><li>PSCO2 and IM69D sensors</li><li>20000 mAh power bank</li><li>Industrial housing</li></ul> |

**Data Collection:**

During drone flights in Athens, the sensor nodes collected the following parameters:

**(1). $CO_2$ Concentration (ppm):** The emission data was collected every one minute.

- **Emission Sources:** Directly influenced by vehicular traffic density, fleet composition, and toll booth activity.
- **External Factors:** Atmospheric conditions, such as sunlight intensity, temperature cycles, and planetary boundary layer (PBL) depth, significantly impact on-road $CO_2$ concentration. Low wind speeds, for example, are correlated with higher concentrations in urban areas.
- **Traditional Modeling Context** :

➢ *Microscopic Models*: Require detailed data such as vehicle kinematics (speed, acceleration), vehicle specifications, and road conditions.
➢ *Macroscopic Models:* Use aggregated traffic data (e.g., average speed, vehicle count, fleet composition) and are more applicable for larger regions.

**(2). Noise Levels (dB):** Average and peak noise values were recorded every 10 seconds.

- **Peak noise levels:** Capture transient events such as vehicle acceleration, honking, or toll operations.
- **Average noise levels:** Indicating average traffic activity.
- **Noise Emission Components:**
  ➢ *Rolling Noise*: Arising from road-tire interaction; influenced by pavement type, slope, and weather conditions.
  ➢ *Propulsion Noise:* Includes contributions from the exhaust, engine, and other mechanical components. Factors such as vehicle type, maintenance, and dynamics (e.g., speed, acceleration) play a significant role.
- **Noise Propagation Factors:** City topography (e.g., building proximity, height); Ground surface and atmospheric conditions (e.g., temperature, wind speed).

**Data Cleaning and Processing:**

- **Timestamp Alignment:** To ensure data quality and consistency, the $CO_2$ concentration and noise peak values were aligned with the timestamps of noise average values in the analysis.
- **Anomaly Detection:** Outliers caused by sensor malfunctions or environmental interferences were flagged and excluded.
- **Integration with Traditional Models:** Real-time sensor data was complemented with insights from traditional vehicular emissions models to provide a more holistic analysis.

**Data Analysis:**

Post-cleaning, the data was analyzed to uncover temporal patterns and multi-modal correlations:

- **$CO_2$ Emissions:** Plots of $CO_2$ concentration over a 24-hour period revealed diurnal patterns influenced by:
  ➢ Traffic density peaks.
  ➢ Toll booth activity.
  ➢ Environmental factors such as sunlight intensity and wind conditions.
- **Noise Levels:** Noise trends highlighted the interplay of rolling and propulsion noise components:
  ➢ Rolling noise dominated during steady traffic.
  ➢ Propulsion noise spikes were observed during vehicle acceleration or stop-and-go situations.
- **Multi-modal Insights:**

> ➢ Combined plots of $CO_2$ and noise levels illustrated the synchronized impact of traffic activity on emissions and noise pollution. These insights provide critical information for designing mitigation strategies tailored to urban environments.

By integrating advanced sensor data with traditional modeling approaches, the DELPHI system offers a comprehensive understanding of the environmental impact of vehicular traffic in urban areas. It emphasizes the importance of considering both localized measurements and broader atmospheric influences in the assessment of $CO_2$ emission and noise levels.

### 4.2.2 Classification/prioritization

The monitoring system captured multi-modal environmental data during drone flights. This section identifies influencing factors and a hierarchical framework of variables and criteria to ensure accuracy and relevance in understanding $CO_2$ emissions and noise levels.

**Effect parameters for the environmental data:**

**(1). Factors for CO2 Emissions:**
- **Microscopic Variables:**
    - ➢ *Vehicle Dynamics:* Speed and acceleration influence emission rates.
    - ➢ *Vehicle Information:* Type, model year, and fuel type are critical for determining emissions characteristics.
    - ➢ *Road Information:* Pavement type and road slope affect fuel consumption and emissions.
- **Mesoscopic Variables:**
    - ➢ *Traffic Dynamics:* Link-by-link average speed; number of stops and delay time for stopped vehicles.
- **Macroscopic Variables:**
    - ➢ *Aggregated Traffic Data:* Average speed of all vehicles; number of vehicles, vehicle kilometers travelled (VKT), representing traffic flow over time.

**(2). Factors for Noise Levels:**
- **Individual Sound Power Emission:**
    - ➢ *Rolling Component:* Influenced by speed, acceleration, vehicle type, tire type, pavement type, road slope, and weather conditions.
    - ➢ *Propulsion Component:* Linked to speed, acceleration, and vehicle type; includes contributions from the engine, exhaust, and mechanical systems.
- **Noise Propagation Factors:**
    - ➢ *Topography:* Geometric location of buildings, height, ground surfaces, and the presence of trees or barriers.
    - ➢ *Atmospheric Conditions:* Temperature, wind speed, and humidity directly influence sound propagation.

**Correlation Analysis Goals:**

The correlation analysis seeks to establish relationships between emissions and noise by considering:

- **$CO_2$ and Noise Interdependence:**
  - Investigate correlations between higher noise levels and increased $CO_2$ emissions as indicators of heavy vehicular activity.
  - Determine whether synchronized fluctuations in noise and emissions data reveal patterns in traffic flow and environmental impact.
- **Influence of External Conditions:**
  - Assess how temporal (e.g., weather conditions, traffic peaks) and spatial (e.g., sensor placement, topography) factors modify the measured variables and correlations.

**Prioritization Criteria:**

To ensure a robust analysis, the following criteria guide the prioritization of data collection and processing:

- **Accuracy of Emission Data:** $CO_2$ Concentration is prioritized as the primary indicator of environmental impact. Accurate readings are crucial for reliable evaluation and modeling of emission patterns.
- **Relevance of Noise Data:** Noise serves as a secondary but essential parameter for understanding traffic dynamics and ambient environmental conditions. Its relevance lies in complementing $CO_2$ data to provide a holistic view of traffic-related environmental impact.
- **Variable Hierarchies:** Microscopic, mesoscopic, and macroscopic variables are analyzed in layers to ensure both granular and aggregated insights. Combining these perspectives offers a comprehensive understanding of traffic behavior and its environmental effects.
- **Time Synchronization:** Ensuring all sensor data is aligned to a common time reference is fundamental for accurate multi-modal correlation analysis.

The integration of micro-, meso-, and macro-level variables, combined with real-time environmental data, enables the system to effectively analyze $CO_2$ and noise emissions. By incorporating detailed parameters such as vehicle dynamics, traffic conditions, and environmental factors, this approach provides a nuanced understanding of the environmental impact of traffic. The system's focus on accuracy, relevance, and synchronization ensures the reliability of insights, supporting emissions mitigation strategies and sustainable urban traffic management.

### 4.2.3 List of factors addressed in DELPHI optimisations

The DELPHI monitoring system incorporates multiple factors to enhance the efficiency and sustainability. These optimisations are essential for reducing resource consumption, improving data management, and ensuring robust performance in real-time environmental scenarios.

**Edge Sensor Optimisation:**

- **Efficient Multi-Modal Sensing:** The integration of $CO_2$ sensors (PSCO2) and microphones (IM69D) enables simultaneous collection of key environmental parameters—$CO_2$ concentration and noise levels—with minimal hardware resources.
- **Low-Power Communication Protocols:** The sensor nodes utilize Sub-GHz communication for efficient, low-energy data transmission to the Raspberry Pi-based gateway. It minimizes energy consumption during data transmission, extending battery life and ensuring sustainable operations.
- **Industrial Housing for Longevity:** Industrial-grade housing protects sensors from harsh outdoor conditions, reducing the frequency of maintenance and replacements, indirectly optimizing resource use.

**Edge Cloud Optimisation:**

- **Localized Data Storage:** The Raspberry Pi-based gateway employs USB storage for local data logging. This allows for temporary offline storage in the event of connectivity disruptions, reducing dependency on continuous cloud access and ensuring no data is lost.
- **MQTT Protocol for Cloud Communication:** Using the MQTT protocol, the system facilitates efficient and reliable data transfer to the cloud with minimal bandwidth usage.
- **Task Offloading:** Non-critical computational tasks, such as detailed correlation analysis and long-term data archiving, are offloaded to the cloud. This ensures that the edge devices focus on real-time data acquisition, minimizing the computational load on resource-constrained edge hardware.

**Incorporation of Multi-Scale Variables:**

**(1). CO2 Emission**:

- Microscopic Variables: Vehicle Dynamics, Road Information, Vehicle Information
- Mesoscopic Variables: Fuel Type Distribution, Year Distribution

**(2). Noise Levels:**

- Individual Sound Power: Rolling Component, Propulsion Component
- Noise Propagation: Topography, Atmospheric Conditions

**System-Level Optimisation:**

- **Scalable Architecture:** The system supports the addition of sensor nodes without major modifications, optimizing resource reuse and enabling expansion for broader monitoring applications.
- **Energy Efficiency:** The edge sensors are powered by long-lasting power banks. Additional energy savings are achieved through optimized transmission protocols and sensor sleep cycles, extending operational periods.

**Real-Time Operation Mode Adjustments:**

- The sensor nodes are designed to operate in both fast and slow modes, allowing to adjust data collection frequency based on requirements. This flexibility ensures efficient resource utilization while meeting the demands of environmental monitoring.

By incorporating edge sensor, edge cloud, and system-level optimisations alongside a framework of multi-scale variables, the DELPHI monitoring system provides a comprehensive, adaptable, and sustainable solution for real-time environmental monitoring. These enhancements ensure efficient resource use, reliable data acquisition, and scalability, aligning with the project's goals of cost-effectiveness and environmental responsibility.

## 4.3 Causal reasoning techniques and AI/ML-powered decision support with predictive capabilities

### 4.3.1 Preliminary list of factors

The related task has two objectives. The first objective focuses on detecting traffic congestion and identifying the propagation sources using data from various sources. Additionally, the task aims to propose solutions that enable responsive and predictive optimisation.

Traffic congestion and its propagation can be effectively analysed by monitoring several key parameters, as identified in existing literature. One critical factor is vehicle trajectories and speeds, which provide insights into speed profiles and acceleration or deceleration patterns. Stop-and-go behaviours, often visualized through time-space diagrams, can indicate the presence of congestion hotspots.

Another significant parameter is the density of vehicles within a given area. High vehicle density combined with reduced flow often points to congestion build-up. Similarly, travel times and delays offer valuable information; comparing observed travel times with expected baseline values helps identify areas experiencing significant delays, which may signal upstream congestion propagation.

Another critical parameter for traffic congestion and passengers' safety is the road, tunnels, and bridges condition in terms on assessing the severity of structural cracks that lead to loosen the strength and stiffness of structure. These cracks often lead to the acceleration of structure dereliction; therefore the prediction of structure cracks is important for the safety of movers and for the maintenance costs associated with repairing them.

Additional indicators include queue lengths at junctions, where long vehicle queues during peak times reflect congestion severity. Lastly, lane utilization ratios, or the distribution of vehicles across lanes, can reveal uneven usage that contributes to bottlenecks and reduced efficiency in traffic flow. These parameters, when analysed

collectively, provide a comprehensive understanding of congestion dynamics and propagation patterns.

The second objective involves developing functionalities for forecasting passenger and freight mobility flows, as well as travel times, across various scenarios. The parameters relevant to this aspect align with those defined in the previous section 4.1 of this report (DELPHI Task 4.2). However, they will be assigned different values to facilitate testing across multiple scenarios.

By leveraging these parameters, the solutions designed under Task 4.4 will ensure robust predictive capabilities and effective optimisation strategies tailored to diverse use cases.

The deployment of cameras and sensors along the ATD Highway provides a comprehensive, real-time view of the road network's status. Through these devices critical data points such as traffic density, vehicle speeds, weather conditions, and the structural health of road network, are captured. By analyzing these data, the optimisation solution that we provide through Delphi-novelty can identify bottlenecks, accidents, or network failures (potholes, cracks, closed lines) that could potentially increase the risk of the followed route. This dynamic information supports an overarching understanding of current conditions, enabling timely responses and guiding drivers toward optimal routes.

## 4.3.2 Classification/prioritization

The most commonly used parameters in traffic analysis provide each unique insights into congestion dynamics and flow efficiency. Vehicle speed profiles reveal patterns of acceleration, deceleration, and potential bottlenecks. Together with flow and density of vehicles (the three fundamental parameters of traffic flow), they help to quantify traffic volume and assess critical thresholds where and when congestion might occur. Then, the rest of the factors such stop-and-go patterns, queue lengths, travel times and delays can build a comprehensive picture of traffic conditions.

The cameras and sensors installed on the ATD Highway serve as increase the robustness of the optimisation framework, leveraging real-time data to enhance decision-making processes. These devices continuously feed information to an AI/ML-powered decision-support system, enabling the understanding of the dynamic changes on the field. Cameras equipped with advanced computer vision algorithms can identify traffic patterns, detect anomalous behavior and assess vehicle flow dynamics at high precision. Sensors embedded in the road surface monitor parameters such as weight distribution and vibrations, providing early warnings about potential infrastructure wear or damage. By integrating these data streams into a centralized platform, the optimisation system gains the ability to model traffic behavior and infrastructure health with high accuracy. Using causal reasoning techniques, the system identifies not only

what is happening but also why it occurs, uncovering underlying factors such as recurring bottlenecks or weather-related disruptions.

The integration of cameras and sensors elevates the efficiency of route planning and traffic management by enabling real-time feedback loops. This data-driven approach not only streamlines traffic flow but also improves safety and minimizes environmental impact by reducing idle times and emissions.

### 4.3.3 List of factors addressed in DELPHI optimisations

All the aforementioned factors will be analyzed, when applicable and based on data availability, to provide a comprehensive assessment of traffic conditions.

# 5. DELPHI Innovations

## 5.1 Integrated freight and passenger transportation optimisation

The concept of combined passenger-freight transportation, as previously discussed, has sparked extensive research from various perspectives, encompassing both qualitative and quantitative approaches. A comprehensive literature review by Elbert and Rentschler (2022)[50] examines, among other aspects, the optimisation and solution methodologies employed in quantitative studies. These methodologies reflect the unique characteristics of the planning and scheduling problems encountered in this field.

*Table 1 - Summary of quantitative approaches of the problem of passenger-freight combined transportation optimisation[51]*

| Reference | Problem | Mode | Sharing | Model | Objective | Solution | Data | Network | STU | Last Mile |
|---|---|---|---|---|---|---|---|---|---|---|
| **Behiri et al. (2018)[52]** | Freight Rail Transport Scheduling Problem (FRTSP) | Light Rail | Vehicle | MIP | Minimize total waiting time of demands at stops | Custom Heuristic | Paris, France | Single Line | yes | N/A |
| **Cheng et al. (2018)[53]** | Network Design | Bus | Wagon | MIP | Minimize total delivery time | Genetic Algorithm | Changsha, China | Network | no | Pickup and delivery vehicles |
| **Fatnassi et al. (2015)[54]** | Stacker Crane Problem | Personal rapid transit | Track | MIP | Minimize costs | Custom Solution Approach | Corby, UK | Network, no transshipment | no | N/A |
| **Ghilas et al. (2016a)[55]** | PDPTW-SL | Scheduled lines | Vehicle | MIP | Minimize costs | Adaptive Large Neighborhood Search | Synthetical data | Network, no transshipment | no | Pickup and delivery vehicles |
| **Ghilas et al.** | PDPTW-SL | Scheduled lines | Vehicle | MIP | Minimize costs | Standard Solver | Synthetical data | Network, no transshipment | no | Pickup and delivery |

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[50] https://www.sciencedirect.com/science/article/pii/S2210539521000626

[51] Table 5, Elbert and Rentschler:
https://www.sciencedirect.com/science/article/pii/S2210539521000626
[52] https://www.sciencedirect.com/science/article/pii/S136655451730162X?via%3Dihub
[53] https://ieeexplore.ieee.org/stamp/sciencedirect_contenthosting&tag=1
[54] https://www.sciencedirect.com/science/article/pii/S0191261515001630-main.pdf
[55] https://www.sciencedirect.com/science/article/pii/s2.0-S0305054816300144-main.pdf

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **(2016b)** [56] | | | | | | | | | vehicles |
| **Ghilas et al. (2016c)** [57] | PDPTW-SL | Scheduled lines | Vehicle | Two-Stage Stochastic Programming | Minimize costs | Adaptive Large Neighborhood Search and Sample Average Approximation | Amsterdam, Netherlands | Network, no transshipment | no | Pickup and delivery vehicles |
| **Ghilas et al. (2018)** [58] | PDPTW-SL | Scheduled lines | Vehicle | MIP | Minimize costs | Branch and Price | Synthetical data | Network, no transshipment | no | Pickup and delivery vehicles |
| **Ji et al. (2020)** [59] | Hub Location Problem | Light Rail, taxi | Vehicle Wagon | MIP | Minimize costs | Genetic Algorithm | Shanghai, China | Network | yes | Taxis, Trucks |
| **Pternea et al. (2018)** [60] | VRP | Bus | Vehicle Wagon | MIP | Minimize costs | Standard Solver | Columbus, Ohio | Network, no transshipment | no | Pickup and delivery vehicles |
| **Masson et al. (2017)** [61] | VRP | Bus | Vehicle Wagon | MIP | Minimize the number of vehicles and costs | Adaptive Large Neighborhood Search | La Rochelle, France | Single Line | yes | Bike |
| **Mourad et al. (2020)** [62] | PDPTW-SL | Scheduled lines | Wagon | Two-Stage Stochastic Programming | Minimize costs | Adaptive Large Neighborhood Search and Sample Average Approximation | Synthetical data | Network | Yes | Robots |
| **Ozturk and Patrick (2018)** [63] | Generalized Allocation Problem | Light Rail | Track | MIP | Minimize total tardiness of deliveries and the number of trains | Custom Heuristic | Synthetical data | Single Line | no | N/A |

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[56] https://ct.prod.getft.io/bE_ZwF_aaiV6wGNU

[57] https://www.sciencedirect.com/science/article/S0191261515300485-main.pdf

[58] https://doi.org/10.1287/trsc.2017.0798

[59] https://doi.org/10.1155/2020/6039032

[60] https://www.researchgate.net/Feasibility-Study-for-Last-Mile-Synergies-between-Passenger-and-Freight-Transport-for-an-Urban-Area.pdf

[61] https://doi.org/10.1007/s13676-015-0085-5

[62] https://doi.org/10.1080/00207543.2020.1746850

[63] https://doi.org/10.1016/j.ejor.2017.12.010

| Pimentel and Alvelos (2018)[64] | Assignment and synchronization problem | Bus | Wagon | MIP | Minimize service time | Standard Solver | Synthetical data | Network, no transshipment | yes | Pickup and delivery vehicles |
|---|---|---|---|---|---|---|---|---|---|---|
| Xie et al. (2020)[65] | Transit crowding model and bottleneck model | Light Rail | Track | MINLP | Maximize consumer surplus (welfare) | Analytical | Synthetical data | Single Line | no | N/A |
| Zhao et al. (2018)[66] | Hub Location Problem | Light Rail | Wagon | MIP & TOPSIS | Minimize total distance from demand sites to hubs | Standard Solver | Shanghai, China | Network | no | Motorcycles small trucks |
| Zhao et al. (2019)[67] | VRP | Light Rail | Wagon | MIP | Minimize total delivery time | Genetic Algorithm | Shanghai, China | Single Line | no | Motorcycles small trucks |

By going through the above summary of research works, we can see that the problem is addressed at different levels and by various points of view. Often, the focus is on the strategic design of the supporting infrastructure, such as for the location of warehouses or distribution hubs, which also consider the existing supportive public transport system infrastructure (rail/metro/bus lines, plans, stops etc.), such as in Ji et al. (2020)[68]. Zhao et al. (2018)[69] designed a metro-integrated logistics system which was modelled as a network flow problem. Fare regimes are also addressed and analyzed in terms of their welfare effect (Xie et al, 2020)[70]. Most of the references in Table 1 model a problem in the operational level, while many of them address the VRP or one of its variants. Vehicle and passenger/package assignment is usually part of the problem modeling. As highlighted also by Elbert and Rentschler (2022)[71], the works of Ghilas et al. (2016a[72], 2016b[73], 2016c[74]) are worth noting. They introduced the pickup and delivery problem with time windows and scheduled lines, which aims at routing a set of vehicles to points of parcel transport requests, from their origin to destination, by

[64] https://doi.org/10.1016/j.trpro.2018.09.010
[65] https://doi.org/10.3390/su12072758
[66] https://doi.org/10.1016/j.tust.2018.06.024
[67] 10.3390/su11030758
[68] https://doi.org/10.1155/2020/6039032
[69] https://doi.org/10.1016/j.tust.2018.06.024
[70] https://doi.org/10.3390/su12072758
[71] https://www.sciencedirect.com/science/article/pii/S2210539521000626#bb0385
[72] https://www.sciencedirect.com/science/article/pii/S0305054816300144-main.pdf
[73] https://doi.org/10.1080/03155986.2016.1166793
[74] https://www.sciencedirect.com/science/article/pii/S0191261515300485

utilizing the scheduled public transport as part of their journeys. They extended their work by integrating stochastic demands and developing a heuristic for solving the problem, as well as trying to develop an exact algorithm for the basic problem.

A wide array of algorithms and solution techniques has been applied to address the variants of the typically NP-hard scheduling and planning optimisation problems involved in combined passenger and freight transportation. These efforts, as summarized in Table 1 above (Table 5 from Elbert and Rentschler (2022)[75]), aim to optimize different aspects of combined transport operations. The methods employed include custom-developed heuristics, well-established metaheuristic algorithms such as Genetic Algorithms, Adaptive Large Neighborhood Search, Branch and Price, and, in some cases, even analytical solutions. These approaches are designed to identify "optimal" values for a range of decision variables, either by minimizing the total cost of the associated process (e.g., logistics plan, supply chain, routing) or by maximizing its performance, as measured through a specific Key Performance Indicator (KPI). In the works of Behiri et al. (2018)[76] and Ozturk and Patrick (2018)[77], the same problem is seen through the lens of general resource sharing, with the aim of optimizing the deployment of trains and railway cars or in Pimentel and Alvelos (2018)[78], balancing the freight loads with the system's capacity and scheduling the distribution within the network in due time to service customers.

In terms of optimisation methodologies that are commonly applied in this problem, it can be said that the selection of a specific solution approach is in principle determined by the special characteristics of the problem formulation of each case. In many instances, the problem is formulated as a specialized version of the Vehicle Routing Problem (VRP). Mixed-integer linear programming (MILP) formulations are commonly employed, as they offer a range of solution methods that can guarantee optimality under certain conditions. In Table 1 above, the related research works are analyzed with reference to the mathematical problem formulation they propose, the modeling structure, the objective function to optimize and the selected optimisation method.

Within DELPHI project, the formulation of this problem focuses more on the strategic and tactical goals, by focusing on the optimized location of micro-hubs (meeting points of conventional trucks and metro lines) and the assignment of fleet and capacity to different locations. Given that, for security reasons, freight is prohibited by law to be transferred together with passengers, we assume in this work that freight is using the same metros but at a different time than passengers, thus overpassing this limitation.

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[75] https://www.sciencedirect.com/science/article/pii/S2210539521000626#bb0160
[76] https://doi.org/10.1016/j.tre.2018.05.002
[77] https://doi.org/10.1016/j.ejor.2017.12.010
[78] https://doi.org/10.1016/j.trpro.2018.09.010

Both problems are special cases of the Generalized Assignment Problem (GAP). The formulation follows is a two-layer structure, where Continuous Approximation is utilized for approximating the costs of routing couriers in the lower layer assignment decisions, while strategic goals of the hub locations are formulated as a Mixed-Integer Linear Problem (MILP). In this way, the problem formulation incorporates both strategic and tactical/operational objectives, while applying the proposed methodology in field tests, something that is generally rare in the existing literature.

At the last step of the integrated freight and passenger transportation optimisation algorithms, a multi-stakeholder optimisation framework for micro-mobility route choice and last-mile delivery in urban environments will be designed. The framework incorporates data that have been collected offline using swarms of drones on:

- traffic conditions,

- noise and $CO_2$ pollution levels via estimating vehicular emissions, and

- road safety to balance the competing preferences of delivery companies and last-mile delivery people.

The method will aim to simultaneously minimize:

- travel time

- exposure to vehicular emissions, and

- traffic safety risks

by defining a composite objective function with distinct weight parameters for each stakeholder. Delivery companies will aim to prioritize operational efficiency and environmental impact, while last-mile delivery people will emphasize on personal safety and least exposure to emissions. Constraints that will be specific to stakeholder priorities will be integrated, such as maximum allowable travel time, pollution thresholds, and acceptable safety risks. The final aim of the methodology will be to demonstrate the system's ability to propose routes that align with both company goals and vehicle operator well-being, enabling sustainable, efficient, and safe urban logistics. This approach will highlight the feasibility of integrating advanced decision-making tools into smart city ecosystems to address the challenges of urban population growth, traffic congestion, and environmental degradation.

## 5.2 Emissions and noise estimation

The relationship between traffic-related $CO_2$ emissions and their impact on atmospheric $CO_2$ concentrations in urban environments is yet to be fully understood. While models for estimating vehicular emissions have been developed and perfected in recent years, linking these emissions to local atmospheric concentrations requires a deeper understanding of urban $CO_2$ dispersion influenced by

complex urban airflow, meteorological conditions, and urban landscape. While urban $CO_2$ concentration is mainly shaped by factors such as diurnal cycles driven by sunlight and temperature variations, as well as wind conditions, which can either facilitate dispersion or exacerbate accumulation under low wind scenarios, previous efforts have highlighted the influence of traffic density on $CO_2$ distributions at street level. Furthermore, data-driven models to predict $CO_2$ concentrations using traffic and urban $CO_2$ background measurement have been proposed in the literature. This project aims to contribute to understanding the gap between $CO_2$ emissions and concentration by integrating advanced modelling techniques using meteorological data to isolate traffic emissions impact on urban $CO_2$ concentration. As the literature review has revealed, $CO_2$ concentration is dominated by atmospheric diurnal conditions and these factors are essential to modelling the correlation between emissions and conditions. Although the relationship between $CO_2$ concentration and traffic has been proven positive in the long term (Gratini and Varone, 2005[79]; Nejadkoorki et al., 2008[80]), the immediate response traffic has on local $CO_2$ concentration is yet to be comprehended it depth. Hence, the partners of DELPHI explore this relationship as well as the influence of noise in the context of the Athens use case by combining an edge local system with $CO_2$ sensors and microphones with drone flights. The data of the local system will be leveraged to train and improve AI models that will be later on used to determine $CO_2$ and noise pollution only based on the data from the drones. Moreover, traffic variables, such as traffic density, traffic flow, and estimated $CO_2$ emissions, will be included in the model.

## 5.3 Causal reasoning techniques and AI/ML-powered decision support with predictive capabilities

Another innovation introduced into the DELPHI project is monitoring mobility through the use of drone-collected trajectory data. Drones offer a unique advantage by providing an aerial perspective that allows for continuous, large-scale monitoring of traffic dynamics - something traditional methods like ground-based sensors or cameras cannot achieve. This aerial view allows for a more comprehensive understanding of congestion and the factors contributing to it.

The key parameters that we aim to analyse using drone data include:

**Vehicle Trajectories and Speeds:** Drones capture detailed speed profiles and acceleration/deceleration patterns of every vehicle on the road. This data can reveal detailed stop-and-go patterns, which are key indicators of congestion. Multi-lane time-space diagrams can further help identify these congestion points more effectively than

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[79] https://www.sciencedirect.com/science/article/pii/S1352231005000609
[80] https://www.sciencedirect.com/science/article/pii/S0048969708007985

usual visualisations. Moreover, they will detect inefficient lane usage that may contribute to congestion, such as lane-blocking or uneven traffic flow. At the same time, as the environment of the vehicle is also captured, the source of these patterns can be detected.

**Vehicle Density and Flow:** Drone footage enables estimation of vehicle density and flow, at any part of the network they are observing. For example, a "virtual" loop detector can be placed at any entrance/exit of an intersection to get the relevant traffic measures.

**Queue Lengths at intersections:** Drones can measure the extent of vehicle queues, especially during peak hours. This allows for better understanding of where and when bottlenecks occur and how long they last.

**Interactions between vehicles and vulnerable road users (VRUs):** Drones can identify locations where vehicles and VRUs (such as pedestrians) frequently interact, which can cause delays in traffic flow. Identifying these conflict points can help authorities focus on safety and mobility optimisation.

The parameters outlined in the analysis can be selectively integrated into a decision support system based on the specific use case, available infrastructure, traffic environment, and stakeholder priorities. Not all parameters will be equally relevant or necessary in every scenario. For example, in a port with high pedestrian and vehicular activity, data on conflict points might be prioritized, whereas in an urban motorway with heavy vehicular traffic, parameters like vehicle density or queue lengths at merges may take the lead. Some more specific examples follow below:

- Integrating vehicle speed profiles, flow and density measurements into such systems can be achieved by linking them to real-time traffic management platforms. This can help identify congestion zones through real-time monitoring and predictive modelling. For example, by using speed, flow and density estimations from static cameras to identify stop-and-go patterns, traffic controllers can notify drivers to alternative routes when approaching intersections or merges. Especially during peak hours, the inclusion of these metrics allows for more precise optimisation strategies, reducing congestion and improving flow.

- Queue Lengths at Junctions: Similarly, queue lengths at merges can provide valuable insight into bottlenecks or lane utilisation. These data points can be fed into existing models to predict future congestion and optimize control systems to avoid the creation of bottlenecks. Additionally, it can help with planning infrastructure investments, such identifying lanes that are being underutilized (or overly congested) and dynamically assigning them, instead of adding extra lanes.

- Identifying conflict points where vehicles and pedestrians frequently interact is critical for improving traffic operations and road safety. For instance, during the embarkation of a boat or simultaneous loading and unloading of passengers, decision support systems can recommend targeted safety measures. These may include implementing improved pedestrian crossings, introducing traffic-calming strategies, or increasing surveillance to manage interactions effectively. Such recommendations aim to enhance safety and streamline traffic flow, tailored to the specific challenges of special traffic environments.

# 6. Conclusions

This deliverable report provides valuable insights on how to address the complexities of multi-modal transport optimisation while focusing on sustainability in all its forms: environmental, social and financial. It performs a detailed review of state-of-the-art methods and techniques, and it explores which key parameters are currently used in different optimisation studies in the field. Following that, the classification and prioritization of key factors take place. The report, through the application of novel approaches in multi-modal sensor correlation, emissions and noise estimation and AI/ML powered decision-support, describes how the DELPHI innovations aim to address the complex challenges of multimodal passenger and freight integration. The holistic approach to multimodal transport optimisation that this report outlines can be useful for a wide range of stakeholders, including researchers, policy and decision makers, transport planners and practitioners. Last but not least, the parameter selection that takes place, provides the basis for the development of the DELPHI decision support system.