



OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Project deliverable D4.1

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

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TABLE OF CONTENTS

TABLE OF CONTENTS	4
LIST OF FIGURES	6
LIST OF TABLES	7
LIST OF ABBREVIATIONS AND ACRONYMS	8
PROJECT EXECUTIVE SUMMARY	9
DELIVERABLE EXECUTIVE SUMMARY	10
1 INTRODUCTION	11
1.1 MAPPING FEDORA OUTPUTS	11
1.2 DELIVERABLE OVERVIEW AND REPORT STRUCTURE	12
1.2.1 <i>Deliverable Overview</i>	12
1.2.2 <i>Report Structure</i>	13
2 SOCIAL OPTIMUM MODELS FOR MULTIMODAL NODES AND CORRIDORS	14
2.1 ANALYSIS OF THE FRAMEWORK CONDITIONS, DEFINITION OF THE OBJECTIVE FUNCTIONS AND FORMULATION OF THE BASIC ALGORITHM	15
2.1.1 <i>Introduction and Problem Statement</i>	15
2.1.2 <i>Traffic Light Phases and Constraints</i>	16
2.1.3 <i>Traffic Arrival and Delay Model</i>	16
2.1.4 <i>Formal Mathematical Formulation</i>	17
2.1.5 <i>Corridor and Network Optimization Extension</i>	18
2.2 COLLECTING AND PROVIDING DATA USING ALL AVAILABLE CHANNELS OF MULTIMODAL TRAFFIC DATA	19
2.2.1 <i>Required input data types</i>	20
2.2.2 <i>Network Topology and Intersection Data</i>	20
2.2.3 <i>Traffic Light Schedules</i>	20
2.2.4 <i>Multimodal Traffic Demand Data</i>	21
2.2.5 <i>Traffic Behaviour data</i>	22
2.2.6 <i>Traffic situation data</i>	23
2.3 TESTING STRATEGY FOR IMPLEMENTATION IN THE VIENNESE PILOT (PILOT#1)	23
2.3.1 <i>Graphical Analysis & References</i>	24
3 DYNAMIC PRICING AND INCENTIVISATION MODELS	27
3.1 DEVELOPMENT AND IMPLEMENTATION OF DYNAMIC PRICING AND INCENTIVISATION MODELS	27
3.2 MOTIVATION: FROM CONGESTION PRICING TO SOCIALLY FEASIBLE TRAFFIC DEMAND MANAGEMENT	28
3.3 FAIRNESS AS A DESIGN AND COMMUNICATION REQUIREMENT	29
3.3.1 <i>Fairness in traffic engineering</i>	29
3.3.2 <i>MOVING BEYOND ONE-DIMENSIONAL EQUITY CLAIMS</i>	29
3.3.3 <i>IMPLICATIONS FOR TASK 4.2 COMMUNICATION</i>	30
3.4 NON-MONETARY ECONOMIC INSTRUMENTS: KARMA AND ARTIFICIAL CURRENCY	30
3.4.1 <i>WHY Alternatives to money are needed</i>	30
3.4.2 <i>Systematic review and design parameters</i>	31

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS



3.4.3	Karma congestion pricing	32
3.4.4	Relationship to tradeable credit schemes	33
3.4.5	Implementation considerations	33
3.5	INDIVIDUALIZATION AND MASS CUSTOMIZATION: THE URBAN PRIORITY PASS	34
3.5.1	from network access pricing to intersection priority	34
3.5.2	Controller and allocation mechanism	35
3.5.3	Case-study evidence	35
3.6	INTEGRATION INTO FEDORA TRAFFIC MANAGEMENT APPLICATIONS	36
3.7	DISCUSSION: EQUITY, ACCEPTANCE, AND LIMITS	37
3.8	CONCLUSIONS AND NEXT STEPS	37
4	MULTIMODAL HUB OPTIMIZATION FOR TRAFFIC MANAGEMENT	39
4.1	DEVELOPMENT OF OPTIMISATION ALGORITHM TO OPTIMISE MULTIMODAL HUBS	39
4.1.1	State of the art and background	39
4.1.2	Solution design and architecture	40
4.1.3	Development of optimisation algorithm to optimise multimodal hubs	41
4.2	DEVELOPMENT OF AN UAV PATH PLANNING MODEL	52
4.2.1	Objective and scope	52
4.2.2	UAV-compatible locations and service definitions	53
4.2.3	UAV and request capacity	54
4.2.4	Euclidean shortest-distance path planning	54
4.2.5	UAV movement and state update	55
4.2.6	Passenger and parcel queues	55
4.2.7	Field-of-view-based data collection	56
4.3	NEXT STEPS – INVESTIGATION OVER THE NICOSIA PILOT	57
5	CONCLUSION	58
6	REFERENCES	59
	ANNEX - ONLINE SOFTWARE RESOURCES AND HOW-TO MANUALS	60

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LIST OF FIGURES

Figure 1: Detailed Signal Plans and Time-Space Diagram. The top section visualizes the precise signal timing phases (green, red, yellow, and red-yellow transitions) for main and cross streets across all 10 intersections. The bottom section depicts vehicle trajectories in both directions (A→J and J→A), demonstrating the progression of the coordinated 'green wave'	25
Figure 2: Convergence behavior of GVNS Optimization. The upper plot illustrates the monotonically decreasing best score (total cost index in seconds) along with individual improvement steps across total execution time. The lower plot displays the corresponding breakdown of vehicle and pedestrian delay times.	26
Figure 3: Task 4.2 research outputs and relation to objectives	27
Figure 4: Six Step Approach For Fair Traffic Engineering [5].....	30
Figure 5: Existing Karma Applications [6].....	31
Figure 6: When Karma works better [7]. The superiority of Karma over money in terms of alignment with needs depends on the distribution of salaries. At a certain level of inequality in the income distribution, Karma performs better than money (Gini coefficient above ~ 0.35).	32
Figure 7: Urban priority pass concept [8].	34
Figure 8: Social welfare analysis of the priority pass for Manhattan [8].....	36
Figure 9: Cluster-based multimodal hub network with multiple mode-specific links between cluster pairs.	41
Figure 10: Average travel time under demand and objective-weight variations.	51
Figure 11: Operating cost per passenger under demand and objective-weight variations.....	51
Figure 12: Number of selected of upgraded hubs.	52
Figure 13: Passenger-link flow composition at reference demand.	52
Figure 14: UAV path planning, repeated services and field-of-view monitoring.....	53



LIST OF TABLES

Table 1: Adherence to FEDORA GA Deliverable & Tasks Descriptions	12
Table 2: Indicative service-unit capacities	42
Table 3: Sets and indices	43
Table 4: Parameters	44
Table 5: Decision variables	44
Table 6: Demand scenarios used in the sensitivity analysis	49
Table 7: Normalised objective-weighted profiles for objective function	49
Table 8: Core performance indicators for the nine illustrative scenarios	51

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LIST OF ABBREVIATIONS AND ACRONYMS

Acronym	Meaning
APC	Automated Passenger Count
CAM	Cooperative Awareness Message
C-ITS	Cooperative Intelligent Transport Systems
EVIS AT	Echtzeit Verkehrsinformation Straße Österreich
FoV	Field of View
FPD	Floating Phone Data
GNSS	Global Navigation Satellite System
GTFS	General Transit Feed Specification
GTFS-RT	General Transit Feed Specification Realtime Reference
GTFS	General Transit Feed Specification
GVNS	General Variable Neighborhood Search
HGV	Heavy Goods Vehicles
kW	Kilowatts
MILP	Mixed Integer Linear Programming
MTM spaces	Mobility and Transport Multimodal Spaces
OD matrix	Origin-Destination matrix
SI	Signalized Intersection
SC	Signalized Corridor
SO	Social Optimum
TAZ	Traffic Assignment Zone
UAV	Unmanned Aerial Vehicles
VND	Variable Neighborhood Descent

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PROJECT EXECUTIVE SUMMARY

The lack of orchestration, structured and standardized integration protocols and metadata descriptors, incorporation of real-world traffic complexities and nuances, underutilization of valuable resources, model uncertainties and integration of micro-mobility services and VRUs result in suboptimal performance in addressing complex issues related to the management of mobility services and infrastructure and a divergence from EU's sustainable mobility targets. FEDORA aims to pave the way towards advanced traffic and network management through the development of a federated spaces platform offering a holistic framework of innovative solutions and services that enable precise and pro-acting sensing of supply and demand, facilitate optimal operation of transport services, and advances learning and evolution in complex environments. At the operational level, FEDORA offers a collaborative space of data that can realize advanced data alchemy processes using interconnected services and tools, a space of advanced traffic management optimisation services and a multi-modal simulation space to create and assess future mobility scenarios. The approach is validated in six thematic demonstrations in Vienna, the Basque Country, Reggio Emilia, Nicosia, Budapest and Denmark, covering varying EU urban and rural contexts, infrastructure maturity levels, multimodal mobility services availability, organisation/operational structures and social conditions. Interaction with existing programmes on road mapping and recommendations at national, EU and global level will be promoted, allowing a multiplication effect of project's results.

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DELIVERABLE EXECUTIVE SUMMARY

This deliverable presents the latest developments in the FEDORA Optimization and Incentivization Models for Multimodal Networks which will be implemented as part of WP4 (Next Generation Multimodal Services Space) to develop and implement advanced routing optimization services and dynamic mitigation plans for multimodal networks. It includes the design and initial development of relevant tools and showcases key achievements so far.

This report presents three core models and components. With the **Social Optimum Model for Multimodal Nodes and Corridors** enables innovative multimodal networks and traffic management services, with a more balanced network availability, towards a “social optimum” based on current and historic traffic situations. The **Dynamic pricing and incentivisation models for traffic management applications** which explore innovative economic instruments and incentive models for traffic demand management, with a particular focus on addressing public resistance and equity concerns related to congestion pricing. It investigates improved communication and fairness approaches, non-monetary mechanisms such as tradable credits and Karma schemes, and smart-city technologies enabling individualized allocation of urban transport resources. As the third model the **Multimodal hub location and services optimisation** that represents a FEDORA software tool to optimize multimodal transport hubs by integrating diverse mobility and traffic data and applying advanced optimization algorithms to identify optimal hub locations, services, and capacities. It also includes a multimodal journey planner and UAV-based traffic sensing and path-planning solutions, supported by simulations and real-world testing to assess traffic impacts and enable user-centric, efficient mobility scenarios.

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1 INTRODUCTION

The goal of this section is to provide a brief outline of the objectives of the specific FEDORA Deliverable, how are those aligned and relevant with the overall project, and what was the approach followed in order to achieve them.

Deliverable D4.1 will collect all results (mid-term results) from the 3 tasks T4.1 to 4.3.

1.1 MAPPING FEDORA OUTPUTS

Purpose of this section is to map FEDORA Grant Agreement commitments, both within the formal Deliverable and Task description, against the project's respective outputs and work performed.

FEDORA ga component title	FEDORA GA COMPONENT OUTLINE	RESPECTIVE DOCUMENT CHAPTER(S)	JUSTIFICATION
DELIVERABLE			
D4.1 - Optimization and Incentivization Models for Multimodal Networks	Optimization and Incentivization Models for Multimodal Networks: Social optimum, dynamic pricing, and multimodal hub optimization models for traffic management (T4.1, T4.2, T4.3)	Whole document	
TASKS			
Task 4.1 - Social optimum models for multimodal nodes and corridors	Analysis of the framework conditions, definition of the objective functions and formulation of the basic algorithm	Section 2.1.	Section 2.1 describes the development and testing of mathematical modelling and advanced optimization techniques to achieve a socially optimal, balanced, and equitable allocation of network resources.
Task 4.1 - Social optimum models for multimodal nodes and corridors	Network Topology and Intersection Data	Section 2.2	Section 2.2 describes provided input data and the different data sources that will be used by the optimization models as well as equipment installed in the vehicles (e.g., C-ITS).

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Task 4.1 - Social optimum models for multimodal nodes and corridors	Testing strategy for implementation in the Viennese pilot (PILOT#1)	Section 2.3	Section 2.3 gives detailed description how the developed optimization models will be tested in the Viennese pilot
Task 4.2 - Dynamic pricing and incentivisation models for traffic management applications	Development and implementation of dynamic pricing and incentivisation models	Chapter	Chapter 3 outlines the development and assessment of innovative, equitable traffic demand management approaches by combining improved public communication of congestion pricing, non-monetary incentive mechanisms such as tradable credits and Karma schemes, and smart-city technologies for individualized allocation of urban mobility resources.
Task 4.3 - Multimodal hub location and services optimisation	implement and test the FEDORA software tool that will optimize multimodal transport hubs for traffic management. The tool will be aligned with the MTM spaces defined in T2.3 to be able to pull multimodal mobility data from the Data Space services developed in WP3	Chapter 4	Chapter 4 outlines the implementation and validation of the FEDORA software tool to optimize multimodal transport hubs and user-centric journeys through integrated mobility and traffic data, advanced optimization and simulation techniques, and UAV-based traffic sensing and monitoring solutions

Table 1: Adherence to FEDORA GA Deliverable & Tasks Descriptions

1.2 DELIVERABLE OVERVIEW AND REPORT STRUCTURE

1.2.1 DELIVERABLE OVERVIEW

This deliverable presents the results of the work carried out within Work Package 4 of the FEDORA project, focusing on the development of optimisation and incentivisation approaches for more efficient, sustainable and user-oriented multimodal transport systems. It brings together the intermediate outcomes of the activities addressing social optimum traffic management, dynamic pricing and incentivisation mechanisms, and the optimisation of multimodal transport hubs.

The deliverable investigates how advanced optimisation methods can support decision-making and traffic management across different spatial and operational levels. At the network level, the developed approaches aim to improve the allocation of limited transport capacity and to balance efficiency objectives with fairness and policy priorities. Dynamic pricing and alternative incentivisation mechanisms are considered as complementary instruments for influencing travel behaviour and supporting the more

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efficient use of transport infrastructure. At the strategic and operational level of multimodal hubs, optimisation models are developed to support decisions regarding hub location, capacity, modal integration and the allocation of passenger flows.

The work reported in this deliverable also establishes the basis for the technical integration of the developed methods into the wider FEDORA ecosystem, including the project's data spaces, simulation environment and pilot activities. The results therefore represent an important step towards an integrated toolbox capable of combining optimisation, demand management and multimodal planning approaches.

As an intermediate project output, the deliverable documents the methodological developments and initial implementation and validation activities undertaken to date. The subsequent phases of the project will further develop, calibrate and validate the proposed approaches using realistic data, simulation environments and pilot-specific use cases.

1.2.2 REPORT STRUCTURE

The report is structured around the three main research and development areas addressed within Work Package 4.

Chapter 1 introduces the deliverable, its objectives, scope and relationship to the overall FEDORA project. It also outlines the contribution of the deliverable to the development of advanced traffic management and multimodal mobility solutions.

Chapter 2 presents the work on social optimum models. It describes the underlying optimisation concepts and methodologies developed to support traffic management decisions, with particular attention to the consideration of different user groups, priorities and system-level objectives. The section also reports on the initial implementation and testing activities.

Chapter 3 focuses on dynamic pricing and incentivisation mechanisms. It examines approaches for influencing user behaviour and allocating scarce transport resources, including fairness-oriented perspectives and alternative, non-monetary incentive mechanisms.

Chapter 4 addresses the optimisation of multimodal transport hubs. It presents the mathematical modelling framework, implementation approach and initial results related to hub configuration, infrastructure requirements, modal integration and passenger-flow allocation.

Chapter 5 summarises the main conclusions and outlines the next steps for further development, integration and validation within the FEDORA pilots and the project's overall technical framework.

Finally, **Chapter 6** provides the list of references.

2 SOCIAL OPTIMUM MODELS FOR MULTIMODAL NODES AND CORRIDORS

The aim of this task is to develop an algorithmic approach for controlling signalized intersections (SI) and signalized corridors (SC) such that the traffic flow is maximized **in a fair manner**. (Note: Maximization of traffic flow is in general equivalent to a minimization of travel times. As we consider constant travel speeds in our model, i.e., we do not interfere with travel speeds of traffic participants, the only factor that can be influenced is the waiting time in front of traffic lights. Therefore, we aim for a minimization of waiting times).

What exactly does “in a fair manner” mean? In our understanding, not all traffic participants should have the same priority when aiming to design a future-resilient multimodal mobility system. E.g., a bus with 30 people inside must have higher priority than an individual motorized vehicle. At the same time, an empty bus being ahead of the time schedule does not need the same prioritization as the before mentioned 30-people bus. That is, fixed prioritisations are a first approach but need to be parametrized. Even more, we think that for each traffic participant and vehicle, it is necessary to give an individual weight in relation to its prioritisation according to the overarching goal of a future-resilient multimodal mobility system. With this background, we assign to each individual a weight which is then used for weighting the waiting time of this individual at traffic lights. We then seek to minimize the weighted sum of waiting times of all traffic participants. This corresponds to what we call **Social Optimum (SO)**.

From a more theoretical viewpoint, a Social Optimum is an extension of a system optimum by adding weights to each individual contributor. A system optimum, in the further, is a system state where the overall objective (e.g., minimization of the sum of travel times) cannot be improved by one (or more) decision changes (e.g., different routes for traffic participants). In contrast to this, game theory defines the so-called user equilibrium which is a system state where no individual can improve their individual objective by an individual decision change (e.g., taking a different route) [1].

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2.1 ANALYSIS OF THE FRAMEWORK CONDITIONS, DEFINITION OF THE OBJECTIVE FUNCTIONS AND FORMULATION OF THE BASIC ALGORITHM

This chapter describes the social optimum algorithm, its background, requirements, needed data, algorithm set-up and the implementation (to be tested in the Viennese Pilot).

- State-of-the-art and background of social optimum algorithms
- Architecture and Set-up of the algorithm
 - Picture of planned architecture
- Data sets (from data space) and its required quality
- Description of the objective function incl. integration of incentive function from ETH
- Interfaces to FEDORA simulation platform for data exchange
- Short description of the Viennese pilot
- Expected results and effects

In a first step, we will introduce an optimisation problem focusing on only one traffic light. In the further, we extend this optimization model towards a corridor, i.e., a set of consecutive traffic lights at intersections.

2.1.1 INTRODUCTION AND PROBLEM STATEMENT

The objective of this problem is to optimize the traffic light signaling program of an intersection to minimize the waiting time of arriving vehicles, cyclists, pedestrians, etc. (referred to broadly as traffic participants).

An intersection consists of a set of movements or directions (e.g., going straight, turning left) across various approach roads. For this modeling framework, the physical grouping of directions onto the same approach road is neglected; each direction is treated as an independent stream.

The traffic light system operates on a fixed total cycle time of $T = 100$ seconds. Within this cycle, each direction transitions through a sequence of standard light phases: Red-Yellow, Green, Flashing Green, Yellow and Red. The durations of the transitional phases are strictly fixed, while the durations of the main “Green and Red” phases are dynamic variables determined by the timing of so-called transition phases (switching events).

2.1.2 TRAFFIC LIGHT PHASES AND CONSTRAINTS

2.1.2.1 PHASE DEFINITIONS AND FIXED DURATIONS

For any given direction, the complete sequence of traffic light states and their structural durations are defined as follows:

1. **Red-Yellow (ΔRY):** Fixed at 2 seconds. It signals the imminent start of the green phase.
2. **Green (g):** Dynamic duration. Variable to be optimized, subject to a minimum duration: $g \geq 5$ seconds.
3. **Flashing Green (ΔFG):** Fixed at 4 seconds. It signals the imminent end of the green phase.
4. **Yellow (ΔY):** Fixed at 3 seconds. It clears the intersection before the red phase.
5. **Red (r):** Dynamic duration. Variable determined by the remainder of the cycle, subject to a minimum duration: $r \geq 5$ seconds.

2.1.2.2 TRANSITION PHASES AND CYCLE LOGIC

The coordination of the intersection is governed by a discrete set of transition phases (or switching events), indexed by $k \in \{1, 2, \dots, K\}$. Each transition phase k is characterized by an absolute timestamp $t_k \in [0, 100)$ within the cycle and is associated with specific directions that either start their active sequence or end it.

The structural rules governing these transition phases are:

Direction Lifecycle: The active phase of any direction always starts at a designated transition phase with the Red-Yellow signal and ends at a subsequent transition phase with the Yellow signal. Multiple directions can start or end during the same transition phase.

Anchoring and Order: Transition phase 1 is fixed as the global anchor at time $t_1 = 0$. All other transition phases $k > 1$ can be shifted in time, but their relative chronological sequence must be preserved:

$$0 = t_1 \leq t_2 \leq \dots \leq t_K < 100$$

2.1.3 TRAFFIC ARRIVAL AND DELAY MODEL

Traffic participants arrive at each direction over an extended time horizon from 0 to $H = 600$ seconds. The arrival times are known deterministically. At any exact second, at most one participant can arrive per direction.

The queuing and clearance mechanism is simplified as follows:

Immediate Clearance: If a participant arrives when the direction's signal is exactly Green, they pass the intersection immediately with zero waiting time.

Waiting and Batch Release: If a participant arrives during any other phase (Flashing Green, Yellow, Red, or Red-Yellow), they must join a queue and wait.

Instantaneous Discharge: At the exact second the signal switches to Green, all accumulated waiting participants in that direction cross the intersection simultaneously.

2.1.4 FORMAL MATHEMATICAL FORMULATION

2.1.4.1 SETS AND PARAMETERS

D	Set of all directions, indexed by i .
K	Number of transition phases, indexed by $k \in \{1, \dots, K\}$.
T	Total cycle length ($T = 100$).
H	Total time horizon for arrivals ($H = 600$).
A_i	Set of arrival times for direction i , where $A_i \subset \{0, 1, \dots, H\}$.
$kstart(i)$	Index of the transition phase where direction i starts its active sequence.
$kend(i)$	Index of the transition phase where direction i ends its active sequence.

2.1.4.2 DECISION VARIABLES

tk	Timestamp of transition phase k , where $tk \in [0, 100]$ for $k = 1, \dots, K$.
gi	Duration of the Green phase for direction i .
ri	Duration of the Red phase for direction i .

2.1.4.3 OBJECTIVE FUNCTION

The objective is to minimize the total accumulated waiting time across all directions over the horizon H :

$$\min \sum_{i \in D} \sum_{a \in A_i} W_i(a)$$

where $W_i(a)$ represents the waiting time of an individual arriving at time a in direction i , derived from the periodic signal state at time $a \pmod T$. In the current described version, all individuals are equally weighted. The actually implemented version will consider appropriate weights based on each individual's characteristics (e.g., mode of transport).

2.1.4.4 CONSTRAINTS

1. Transition Ordering and Bounds:

$$t1 = 0$$

$$tk \leq tk+1 \quad \forall k \in \{1, \dots, K-1\}$$

$$tK \leq 100$$

2. Signal Timing and Interval Continuity:

For each direction i , the start of the green phase depends on the start transition $tkstart(i)$ plus the fixed Red-Yellow shift:

$$tgreen_start(i) = (tkstart(i) + \Delta RY) \pmod{T}$$

The end of the green phase is determined by the end transition phase minus the fixed durations of Flashing Green and Yellow:

$$tgreen_end(i) = (tkend(i) - \Delta FG - \Delta Y) \pmod{T}$$

3. Minimum Phase Durations:

$$gi \geq 5 \quad \forall i \in D$$

$$ri \geq 5 \quad \forall i \in D$$

2.1.5 CORRIDOR AND NETWORK OPTIMIZATION EXTENSION

In a more advanced setting, rather than optimizing a single isolated intersection, we consider a corridor or a network of interconnected traffic lights. In this scenario, the intersections are coupled: the outflow of traffic from one traffic light acts as the deterministic inflow to a specific direction of a downstream traffic light.

2.1.5.1 NETWORK TOPOLOGY AND COUPLING LOGIC

Let N be the set of all intersections (traffic lights) in the corridor, indexed by n . Each intersection $n \in N$ has its own set of directions D_n and its own independent set of transition phase timestamps tn,k .

We define the coupling between intersections using a directed graph where edges represent the links between an upstream direction and a downstream direction:

Let L be the set of links, where a link $l = ((n1, i1), (n2, i2)) \in L$ indicates that the output from direction $i1$ at intersection $n1$ flows directly into direction $i2$ at intersection $n2$.

Each link l is characterized by a constant travel time $\tau_l \geq 0$ (seconds), representing the time it takes a participant to traverse the distance between the two intersections.

2.1.5.2 DYNAMIC INPUT GENERATION (OUTFLOW TO INFLOW)

For directions that are not connected to any upstream intersection, the arrival set An,i remains an exogenous, fixed parameter as defined in Section 3.

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For a coupled direction $i2$ at intersection $n2$ fed by an upstream direction $i1$ at intersection $n1$, the arrival times $An2,i2$ become endogenous dynamic variables that depend entirely on the departure times from the upstream intersection.

The departure time d of a participant arriving at the upstream intersection $n1$ at time $a \in An1,i1$ is determined by the signal state:

$$d(a) = a \quad \text{if signal at } a \pmod{T} \text{ is Green}$$

$$d(a) = t_{\text{green_start}}(n1, i1) + \lfloor a/T \rfloor \cdot T \quad \text{if signal at } a \pmod{T} \text{ is NOT Green}$$

Note: If a participant has to wait, they depart exactly at the next upcoming Green cycle start ($t_{\text{green_start}}$) of that upstream direction.

Consequently, the arrival time at the downstream intersection $n2$ for this participant is shifted by the travel time τ_l :

$$a_{\text{downstream}} = d(a) + \tau_l$$

The set of downstream arrivals is therefore dynamically constructed as:

$$An2, i2 = \{ d(a) + \tau_l \mid a \in An1, i1 \}$$

2.1.5.3 MODIFIED GLOBAL OBJECTIVE FUNCTION

The global optimization goal for the entire corridor is to minimize the sum of all waiting times across all intersections N and all respective directions D_n over the planning horizon H :

$$\min \sum_{n \in N} \sum_{i \in D_n} \sum_{a \in An,i} W_{n,i}(a)$$

where $W_{n,i}(a)$ is the waiting time at intersection n for direction i given an arrival at time a . For coupled directions, this waiting time directly interacts with the upstream timestamps, creating a highly non-linear, interdependent optimization landscape (often solved via coordination mechanisms like 'Green Waves').

2.2 COLLECTING AND PROVIDING DATA USING ALL AVAILABLE CHANNELS OF MULTIMODAL TRAFFIC DATA

This section first introduces the types of data required as input to the social optimum model. It then discusses the possible data sources. Finally, the requirements for the data are presented.

2.2.1 REQUIRED INPUT DATA TYPES

The data categories required can be divided into the following broad categories:

- network topology and intersection data (static)
 - graph model of the corridor
 - model of the intersection including lanes
 - allowed mode of transport for each lane
 - signal groups
- traffic light schedules (static and dynamic)
 - existing traffic light schedules
 - requirements for the traffic light schedules output by the social optimum model
- multimodal traffic demand data (static and dynamic)
 - traffic counts of traffic participants per ingoing lane to the intersection and per considered mode of transport
 - turn probabilities for each mode of transport and each ingoing lane
- travel behaviour data (static)
 - average expected speeds for each mode of transport
- traffic situation data (dynamic)
 - current levels of service for motorized vehicles
 - current average speeds for motorized vehicles

In the following sections, the properties, the quality and availability of this data is discussed in further detail.

2.2.2 NETWORK TOPOLOGY AND INTERSECTION DATA

Network graphs are available from commercial providers and open source. Open Street Map (<https://openstreetmap.org>) is frequently used.

For the **Vienna Pilot**, the Austrian national network graph (Graphenintegrationsplattform, GIP, <https://gip.gv.at>) will be used. This graph is the base for the traffic demand and traffic situation models of ITS Vienna Region. Besides the network topology it contains information on access regulations for passenger cars and heavy goods vehicles, one-way streets, speed limits, reference speeds, lane numbers, and turns amongst others. The GIP graph does not only contain a topological model but also a cross-section model. This is particularly important for pedestrian and cyclist traffic, as the sidewalks and cycle lanes including their properties like width and type of pavement are modelled separately.

In addition to the intersection geometry, lanes and turns that can be obtained from the network graph, the grouping of traffic movements controlled by each signal phase (signal groups). This provides information on which phases allow which lanes to proceed and cross the intersection and is a prerequisite for mapping traffic light schedules onto the intersection and network models. This data is not available at the moment and must be entered manually.

2.2.3 TRAFFIC LIGHT SCHEDULES

Traffic light schedules (signal plans) consist of several programs. Each program has a cycle length and describes a sequence of light phases for each signal group. In addition to cyclical programs (the transition from the last phase back to the first phase is compatible), there can be transition programs. These are used when switching between different cyclical programs, as the end phase of one

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

program does not necessarily match the start phase of the next. For the Vienna Pilot, signal plans are available graphically and must be entered manually into the system.

2.2.4 MULTIMODAL TRAFFIC DEMAND DATA

As the social optimum aims to balance delays fairly across all traffic participants, it has to consider all modes of transport when optimising the signal phases. This requires data on all commonly observed modes of transport at the examined intersections. Model training and calibration need historical data whereas live optimization requires real-time data.

Common sources for traffic demand data are manual or automated traffic counts, traffic surveys, traffic models and floating phone data (FPD).

Data quality and data availability vary greatly not only for different types of data sources, but also for different modes of transport.

Traffic demand models depend on the quality of behavioural data from traffic surveys and demographic data as these are the most important inputs for trip generation. Traffic surveys are usually conducted in intervals of several years and thus, data is often outdated. While statistical data on population, employment and education is usually available, reliable and frequently updated, fine-grained information about shopping, tourism, and recreation facilities is often lacking. FPD provide an additional empirical data source for traffic demand. Whereas potential sample sizes are much larger than for surveys, low positioning accuracy and difficulties with mode detection prove problematic especially in urban settings.

For motorized traffic in urban settings, traffic counts are usually available for relatively few road sections given the extent and complexity of the network. Traffic models provide data for a more extensive network, though the accuracy of the results for specific road sections cannot be validated without counts. For zone-based macroscopic traffic models, calculated traffic flows are not reliable for the local access network in general.

Public transport passenger counts are in most cases available at the operators, they are not, in general, published, though. Automated Passenger Count (APC) systems are widely deployed in buses. Though technically feasible, this data is not used or provided in real time in general. Trams, subway and railway cars, having much longer investment cycles than buses, are less frequently equipped with APC systems. Public transport demand models are available in many major cities, including Vienna.

For bicycle traffic, counts are available (though they are rather scarce in Vienna). Traffic demand modelling for bicycle traffic is not as well established as for motorized traffic yet; route choice is thought to rely on additional parameters like recreational value and properties of the infrastructure whose impact is difficult to quantify [2]. In recent years, cycling infrastructure has been extended and bicycle traffic has increased significantly in many cities, including Vienna, reducing the value of historical data for estimates and predictions.

Reliable data for pedestrian traffic is hard to come by. Traffic surveys usually include pedestrian traffic as a mode of transport, but there are estimates that pedestrian trips (especially short walks) could be underreported by as much as 30% [3]. Given the short distances travelled, the spatial resolution of zone-based macroscopic traffic models is too coarse to generate useful demand data for pedestrian traffic.

For, the **Vienna Pilot**, traffic count data and traffic model data is available for motorized vehicles and public transport.

Historical demand data can be derived from stationary detectors at some locations within the pilot area. This data feeds also into the traffic demand model for Eastern Austria. This model calculates estimated average workday traffic demand. OD matrices are computed for five traffic modes:

- motorized vehicle passenger transport
- public transport
- park & ride
- bicycle transport
- pedestrians

Additionally, freight vehicle demand from a separate freight traffic model is integrated. Traffic assignment is computed for passenger vehicle transport, freight vehicle transport and public transport only. The model network is rather fine-grained and contains most of the local access network in the pilot area; the assignment results for these small roads are not reliable though, in general.

Assignment results are link based, not lane based; lane-based demand must be estimated for multi-lane sections. Turn probabilities can be derived from the model.

Real-time traffic counts are available from the stationary detection within the pilot area. These counts are lane-based; the detectors are placed some 150-250 m before the intersections, though, so lane-based demand at the intersection must be estimated.

Real-time public transport passenger counts are not available in Vienna. Occupancy rates can be estimated from historical passenger data.

There are some bicycle traffic detectors (induction loops and camera-based systems) deployed in Vienna, but none within the pilot area. To make up for the lack of pedestrian and cyclist counts, a newly developed object detection algorithm shall be deployed using imagery from 17 traffic cams installed within the pilot area.

2.2.5 TRAFFIC BEHAVIOUR DATA

The Social Optimum Model needs estimates of average travel speeds for different modes of transport. Travel speeds for motorized vehicles can be derived from FCD measurements or C-ITS CAM data, for instance. Public transport travel times and speeds may be derived from planned and real-time timetable data.

FCD raw data or speed measurements derived from FCD can be purchased from commercial providers or may be provided by taxi operators, ambulances, or company car fleets for instance. Even with low penetration rates, FCD datasets collected over longer periods allow for detailed evaluations of speed distributions for different road sections, weekdays and times of the day.

Quality problems with FCD data may arise from low GNSS accuracy in combination with long sampling intervals that can lead to map matching and routing errors and thus, artifacts and outliers; this can be addressed by proper outlier handling in large historical datasets. Another potential issue is that, due to anonymization, data from heterogeneous fleets may not contain information about vehicle types. Thus, biases towards higher shares of heavy goods vehicles (HGVs), for instance, may go undetected. This is less of a concern in urban settings but may lead to underestimation of average speeds on motorways or rural roads due to the lower maximum speeds of HGVs.

Though the mechanisms behind speed calculation from FCD and C-ITS CAM data are the same, the problems are different in practice. CAMs should be emitted at least once a second, so routing errors arising from long sampling intervals are not a concern. Proper CAMs should also contain the vehicle type. The major problem with CAM data is availability: only few vehicles emit these messages and collecting them requires a specialized short range receiver infrastructure that is only gradually being deployed, whereas FCD positions can be transmitted over almost ubiquitous long range telecommunication networks.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Timetable data usually consists of arrival and departure times at stops and contains route information in many cases (e.g. shapes in GTFS). Times are given in minutes and not in seconds, so speeds calculated from this data may not be very accurate in general. Public transport operators may have more detailed data, but this is not, in general, published. Public transport real-time data is stop-based as well, though some interface standards (e.g. GTFS-RT, VDV 453 VIS) allow for GNSS positions to be transmitted.

For the **Vienna Pilot**, speed measurements from FCD and timetable data are available. C-ITS infrastructure is deployed in the pilot area and can be used for receiving CAM.

ITS Vienna Region has access to FCD raw data from the two major taxi fleets for traffic data calculations and analysis, and additional FCD measurements are available from EVIS AT (Echtzeit Verkehrsinformation Straße Österreich, see <http://evis.gv.at/>), a national cooperation of public road and ITS operators that provides real-time traffic data for Austria.

GTFS Timetable data is published weekly by the consortium of Austrian public transport administrations (Mobilitätsverbünde Österreich, see <https://mobilitaetsverbuende.at/>).

Empirical data for pedestrian and cyclist travel speeds is not available for the Vienna pilot. Reference values from the literature will be used.

2.2.6 TRAFFIC SITUATION DATA

For the Vienna Pilot, traffic situation data is available from the real-time traffic model of ITS Vienna Region. The model outputs are traffic flows, average speeds, traffic densities, and queue lengths on the links of the network graphs as well as levels of service derived from these parameters. The model uses the General Link Transmission Model [4] for dynamic traffic assignment.

Input data are:

- The network graph, including speed and capacity attributes for links and turns
- Base demand for motorized vehicle traffic as OD matrices for three-day types (workdays, Saturdays, Sundays and holidays) and 24 hours of the day
- Real-time traffic count data from stationary detectors
- Real-time FCD
- Impacts from current DATEX II traffic situation records

The model adjusts previously calculated traffic state parameters to the real-time data and propagates the adjusted traffic flows downstream using pre-calculated time-dependent turn rates.

The model covers the higher-level road network of Vienna, Lower Austria and Burgenland in Eastern Austria. The local access network is not included. Values are computed for the whole pilot corridor, but not for some of the lower-level crossing roads.

2.3 TESTING STRATEGY FOR IMPLEMENTATION IN THE VIENNESE PILOT (PILOT#1)

This section outlines the methodological framework implemented for optimizing signal timing plans along arterial corridors. Each traffic signal is parameterized by three key variables: cycle time (c), main-street green time (g), and offset (o). To solve this continuous-discrete optimization problem and minimize total network delay (a weighted index combining vehicle and pedestrian wait times), a metaheuristic framework based on Variable Neighbourhood Search is employed.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

General Variable Neighborhood Search (GVNS): The overarching optimization process is governed by the GVNS algorithm. Starting from an initial baseline signal plan (cycle time $c = 90$ s, main-street green $g = 45$ s, offset $o = 0$ s), the algorithm systematically explores the search space by perturbing current solutions in a Shaking phase. The shaking intensity scales with the neighborhood index $k \in \{1, \dots, k_{\max}\}$. Following shaking, an intensive local search is performed. If a candidate solution yields a strictly lower overall cost index, it is accepted immediately, and the algorithm resets to the first neighborhood ($k = 1$). Otherwise, the shaking strength is intensified ($k \leftarrow k + 1$).

Variable Neighborhood Descent (VND): Serving as the local search engine within GVNS, the VND operates deterministically using a First-Improvement strategy. It sequentially evaluates neighborhood structures N_i . Upon discovering any move that yields an improved objective value, the step is immediately executed and search restarts at the primary neighborhood (N_1). The local search terminates only when no further improvements can be achieved across any available neighborhood.

Moves & Neighborhood Structures: The modification of signal plans is decoupled into specialized Move classes and Neighborhood structures targeting specific control parameters:

Offset Move & Neighborhood (N_1): ShiftOffsetMove adjusts the offset o of an individual intersection by Δo seconds, with automatic modulo normalization to $[0, c)$. OffsetNeighborhood explores discrete offset shifts (e.g., $\Delta o \in \{-5s, -2s, 2s, 5s\}$), while its shaking procedure applies random shifts proportional to the current shaking intensity k .

Transition Move & Neighborhood (N_2): ShiftTransitionMove alters the main-street green duration g by Δg seconds, shifting the phase boundary between main and cross streets. Safety bounds enforce minimum green times (at least 10 s green for both main and cross directions). TransitionNeighborhood generates discrete green-time adjustments (e.g., $\Delta g \in \{-4s, -2s, 2s, 4s\}$) and performs bounded random perturbations during shaking.

2.3.1 GRAPHICAL ANALYSIS & REFERENCES

To test the performance of the approach, different test instances have been generated. As the Viennese pilot case will most probably consist of 10 traffic lights along a corridor, we present some preliminary results for a virtual 10 traffic lights corridor. Figure 1 depicts the results signal plan together with a time-space diagram of vehicles along the corridor. As can be seen, a perfect green wave is the result of the optimization approach. Figure 1 shows the runtime behavior of the chosen optimization approach. Although the overall runtime is about 60 seconds, it can be seen that after only 10 seconds an already good solution is obtained. After additional 10 seconds, a very good solution is already obtained, indicating that the chosen approach is expected to be applicable in a real-world setting where every about 10 minutes a recalculation of the signal plan for the next time period is envisaged. Nevertheless, algorithmic improvements are possible by thinking about additional moves as well as neighborhood structures in order to speed the optimization process up.



Figure 1: Detailed Signal Plans and Time-Space Diagram. The top section visualizes the precise signal timing phases (green, red, yellow, and red-yellow transitions) for main and cross streets across all 10 intersections. The bottom section depicts vehicle trajectories in both directions (A→J and J→A), demonstrating the progression of the coordinated 'green wave'

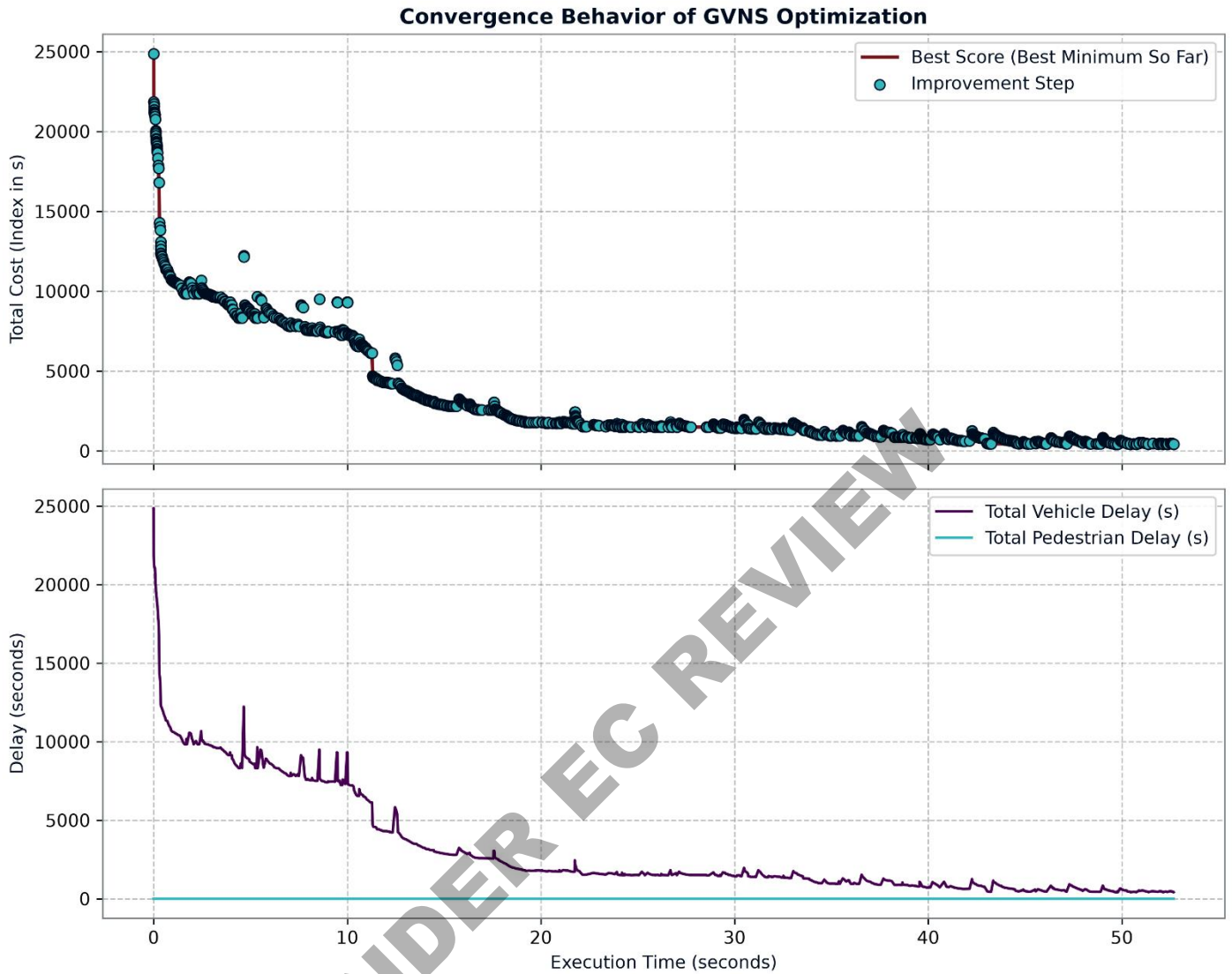


Figure 2: Convergence behavior of GVNS Optimization. The upper plot illustrates the monotonically decreasing best score (total cost index in seconds) along with individual improvement steps across total execution time. The lower plot displays the corresponding breakdown of vehicle and pedestrian delay times.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

3 DYNAMIC PRICING AND INCENTIVISATION MODELS

3.1 DEVELOPMENT AND IMPLEMENTATION OF DYNAMIC PRICING AND INCENTIVISATION MODELS

Task 4.2 investigates dynamic pricing and incentivisation models for traffic management applications. The task is led by ETH, with CRE as participant, and runs from M4 to M29. Its objective is to explore economic instruments for traffic demand management that are effective from a traffic-engineering perspective and socially feasible from a public-acceptance perspective. This is important because road traffic demand management measures, in particular congestion pricing, are widely recognized as effective tools for reducing overuse of scarce urban road capacity, but their implementation is often blocked by public resistance. The most persistent objections concern equity, fairness, and the fear that road access will become a privilege for those with greater financial power.

Figure 3: Task 4.2 research outputs and relation to objectives

Output	Main contribution	Link to Task 4.2 objective
Towards Fair Roads - Manifesto for Fair Traffic Engineering [5]	Quantitative, mode-agnostic fairness framework for infrastructural and behavioural traffic control	Supports objective (i): objective and systematic fairness discussion and public communication
Resource Allocation with Karma Mechanisms - A Review [6]	Systematic review and design-parameter framework for Karma mechanisms	Supports objective (ii): conceptual foundation for artificial currencies and non-monetary markets
Karma Economies for Sustainable Urban Mobility [7]	Karma congestion-pricing model, software framework, and bridge-pricing case study	Supports objective (ii): non-monetary alternative to congestion pricing and tradeable credits
Urban Priority Pass [8]	Reservation-based market for individual prioritisation at signalized intersections	Supports objective (iii): individualization and mass customization of spatio-temporal road resource allocation

Within FEDORA, the work in Task 4.2 therefore followed three complementary research directions. First, ETH developed a systematic way to discuss fairness in traffic engineering and to communicate the benefits and trade-offs of congestion pricing and related traffic management measures. Second, ETH explored non-monetary economic instruments, in particular artificial currencies and Karma mechanisms, as alternatives or complements to conventional monetary pricing and tradeable credit schemes. Third, ETH investigated smart-city-enabled individualization of spatio-temporal road resource allocation through a new market-based concept for individual signal priority, called the Urban Priority Pass.

These directions are not isolated. They form a coherent line of work from public acceptability and fairness, through mechanism design, to implementable smart-city traffic control. The fairness work provides the language and quantitative tools needed to explain why a demand-management policy can be socially justified. The Karma work provides an alternative to monetary congestion pricing when equity objections are too strong. The Urban Priority Pass extends the idea of dynamic incentivisation from area access or route

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

choice to fine-grained intersection control, where individual users or vehicle classes can receive time-sensitive priority in accordance with need, urgency, or policy objectives. Table 3.1 summarizes the main Task 4.2 outputs and their relation to the task objectives.

3.2 MOTIVATION: FROM CONGESTION PRICING TO SOCIALLY FEASIBLE TRAFFIC DEMAND MANAGEMENT

Urban road networks can be understood as scarce public-good infrastructure. They provide accessibility to employment, education, care, shopping, recreation, and social participation, yet their utility diminishes when too many users consume the same infrastructure at the same time. When demand exceeds capacity, congestion emerges. Congestion creates delay costs for users, additional fuel and energy consumption, emissions, noise, safety risks, stress, and economic losses. From a traffic management perspective, the problem is not only that road users are delayed, but that individually rational decisions can lead to a collectively inefficient outcome. Each driver may choose the fastest apparent route or most convenient travel time, while the aggregation of these choices overloads specific links, intersections, corridors, or urban areas.

Traffic demand management aims to align individual incentives with system-level performance. Congestion pricing is a well-established example. By charging for the use of scarce road space, a road authority can discourage low-value trips, encourage changes in route or time of departure, and keep traffic flow below critical capacity levels. In principle, this can improve travel times for the remaining users, reduce total delay, and generate revenues that can be reinvested in transport infrastructure or public transport. From the perspective of economic efficiency, pricing can be very powerful because it allows decentralized decision-making: each user decides whether the trip is worth the charge.

However, real-world implementation of congestion pricing is not determined by efficiency alone. Public debate typically focuses on who pays, who benefits, who has alternatives, and whether the measure treats users fairly. These concerns are legitimate. Monetary prices do not only reflect urgency or need; they also reflect ability to pay. A high-income traveller may easily absorb a charge, while a low-income commuter with poor public transport alternatives may face a substantial burden. This creates a political problem and a normative problem. The political problem is that policies perceived as unfair struggle to obtain public support. The normative problem is that an instrument designed to improve aggregate efficiency can reinforce existing inequalities if its distributional effects are not addressed.

Task 4.2 starts from this implementation barrier. Instead of treating fairness as an afterthought, the task positions fairness as a core design requirement for traffic management. This involves two shifts. The first shift is conceptual: traffic engineering measures should be described as resource allocation mechanisms. Signal control allocates green time and delay. Congestion pricing allocates road access, travel time, financial costs, and revenues. Priority systems allocate delay reductions and waiting time. Once traffic engineering is framed in this way, fairness becomes a question of how scarce mobility resources, costs, and benefits are distributed among users and stakeholders. The second shift is methodological: fairness should be discussed through multiple explicit perspectives, supported by quantitative measures, rather than through one vague statement that a policy is "equitable" or "inequitable". This is the basis for the FEDORA Task 4.2 contribution. The work developed a fairness framework for traffic engineering [5], used it to understand monetary and non-monetary instruments [6, 7], and then explored new smart-city mechanisms for individualized priority [8].

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

3.3 FAIRNESS AS A DESIGN AND COMMUNICATION REQUIREMENT

3.3.1 FAIRNESS IN TRAFFIC ENGINEERING

The work "Towards Fair Roads - Manifesto for Fair Traffic Engineering" argues that traffic engineering has historically focused heavily on efficiency, for example minimizing total travel time, maximizing throughput, or reducing average delay [5]. These indicators remain important, but they are incomplete. A policy can improve average travel time while creating unacceptable waiting times for a minority of users. A signal controller can increase throughput while systematically disadvantaging pedestrians, cyclists, buses, or a particular movement. A pricing measure can reduce congestion while shifting the burden onto users with fewer alternatives. These are not minor communication issues; they are core design issues.

The fairness framework developed in [5] proposes that traffic engineering solutions should be evaluated as allocation mechanisms for fairness-relevant resources. For infrastructural control, the main fairness-relevant resources include delay, waiting time, exposure to pollution, and safety-related burdens. For behavioural control, relevant resources include travel-time costs, financial costs, artificial-currency budgets, access rights, and redistributed revenues. The framework distinguishes between two broad transaction types. Diabetic fairness concerns distributions made by an authority to a population, such as a traffic signal allocating green time. Diorthotic fairness concerns market-like interactions among individuals, such as route choice under road pricing.

This distinction is useful for Task 4.2 because dynamic pricing and incentivisation models often combine both transaction types. For example, a congestion-pricing scheme creates a market-like choice between paying for a faster route or avoiding the charge, but the initial distribution of financial resources and available alternatives is not created by the market itself. A tradeable credit scheme creates an initial entitlement distribution and then allows market exchange. A Karma mechanism creates an artificial budget and allocates access according to past and future consumption of the same resource. A Priority Pass can be allocated centrally by a public authority or through a market with compensation for non-prioritized users.

3.3.2 MOVING BEYOND ONE-DIMENSIONAL EQUITY CLAIMS

A key output of [5] is that fairness should not be reduced to a single metric. Different fairness ideologies emphasize different concerns. An egalitarian view focuses on equal outcomes or low dispersion. A utilitarian view focuses on aggregate welfare. A Rawlsian view focuses on improving the position of the worst-off users. A Harsanyian view considers expected utility behind a veil of uncertainty. Aristotelian and luck-egalitarian perspectives focus on whether differences in outcomes are justified by relevant inputs or whether they reflect arbitrary starting conditions. These perspectives can lead to different conclusions for the same traffic management strategy.

This is particularly relevant for public communication. In congestion pricing debates, opponents and proponents often speak past each other. Proponents highlight efficiency gains, reduced congestion, and revenue use. Opponents highlight affordability, freedom of movement, and distributional burdens. A structured fairness framework allows the debate to become more objective. It asks: Which users are affected? Which resources are allocated? Are we evaluating delay, money, access, pollution, or revenues? Are we concerned with average welfare, the worst-off users, equality of outcomes, or compensation for unequal starting conditions? What redistribution or exemption policies are needed?

The case studies in [5] demonstrate that fairness and efficiency are not always in conflict. In signalized intersection management, there can be an alpha-efficient solution space: many signal settings achieve nearly the same throughput, leaving room to improve fairness without sacrificing operational performance. In static road pricing, a properly selected price can improve system efficiency and several fairness measures at the same time by reallocating road use toward users with higher need. The important conclusion is not that every pricing scheme is fair. Rather, the conclusion is that fairness can be quantified, compared, and incorporated into design.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

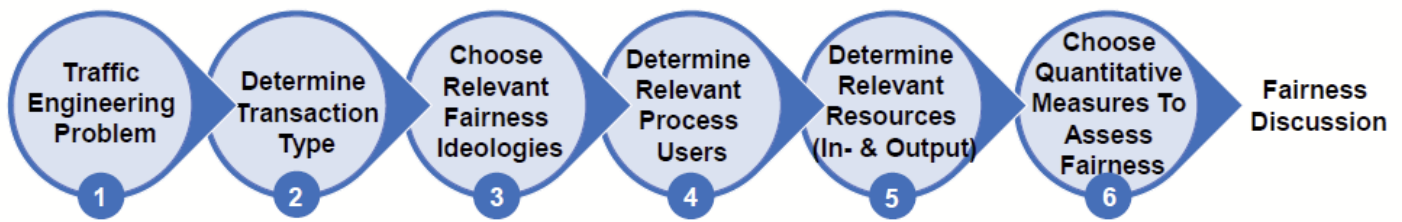


Figure 4: Six Step Approach For Fair Traffic Engineering [5].

3.3.3 IMPLICATIONS FOR TASK 4.2 COMMUNICATION

The first objective of Task 4.2 is to better understand how to communicate the benefits and promote the concept of congestion pricing to the public. The findings suggest that communication should not rely only on aggregate efficiency. A convincing communication strategy should make the distributional mechanism visible.

For a conventional congestion-pricing measure, communication should explicitly state what the charge is intended to achieve, which demand responses are expected, how travel times and reliability are expected to improve, and how revenues are used. Just as importantly, it should explain which users might be disproportionately affected and what compensatory design elements are included. These can include targeted exemptions, mobility credits, revenue redistribution, public transport investment, income-sensitive rebates, or non-monetary alternatives. Without these elements, the public may reasonably interpret pricing as a new financial burden rather than as a traffic management instrument.

For FEDORA, the fairness framework supports the design of transparent and auditable dynamic pricing models. It can be used before implementation to evaluate candidate policies in simulation, during stakeholder engagement to explain trade-offs, and after deployment to monitor whether outcomes align with policy objectives. This is especially valuable for smart-city contexts where automated decision-making may otherwise appear opaque. If an algorithm changes prices, allocates priority, or modifies access rights, users and authorities need a clear account of why the decision is legitimate.

3.4 NON-MONETARY ECONOMIC INSTRUMENTS: KARMA AND ARTIFICIAL CURRENCY

3.4.1 WHY ALTERNATIVES TO MONEY ARE NEEDED

The second Task 4.2 objective is to explore non-monetary economic instruments based on artificial currencies, such as tradeable credit schemes and Karma mechanisms. The motivation is direct: money is a flexible and powerful allocation instrument, but in traffic demand management it can generate equity objections because financial willingness to pay is shaped by unequal income and wealth. In such settings, an efficient monetary market may allocate scarce road capacity to those with the highest value of time, but value of time combines urgency with income. The resulting allocation may therefore reflect financial power as much as actual need.

Artificial currencies offer a way to separate mobility-resource allocation from general purchasing power. Tradeable credit schemes do this by giving users credits or permits that can be used for road access and traded with others. These schemes can cap total demand and create a market for scarce mobility rights. However, tradability can reintroduce equity concerns. Users with lower income may sell credits because they need money, even if they would benefit from travel, while wealthier users may buy additional credits and continue travelling.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Karma mechanisms represent a different class of artificial-currency systems. Karma is a non-monetary, non-tradeable, resource-inherent currency. It can only be gained by producing or conserving a specific resource and only spent by consuming that same resource [6]. In a mobility context, a user may gain Karma by not consuming scarce road capacity at a certain time and spend Karma when consuming the resource becomes important. Because Karma cannot be bought with money, the mechanism changes the user's trade-off. Instead of asking "Is this trip worth the monetary charge compared with everything else I could buy?", the user asks "Is this trip urgent enough to spend my limited mobility budget now rather than save it for a future need?"

3.4.2 SYSTEMATIC REVIEW AND DESIGN PARAMETERS

The Karma review [6] provided a conceptual foundation for this part of Task 4.2. It systematically mapped the Karma literature across domains such as peer-to-peer file sharing, cloud and computational resource sharing, telecommunications, blockchain, social networks, and transportation. The review showed that Karma has been used in several fields, but that terminology and mechanism design choices were fragmented. To support systematic future research, [6] identified core design parameters for Karma mechanisms.

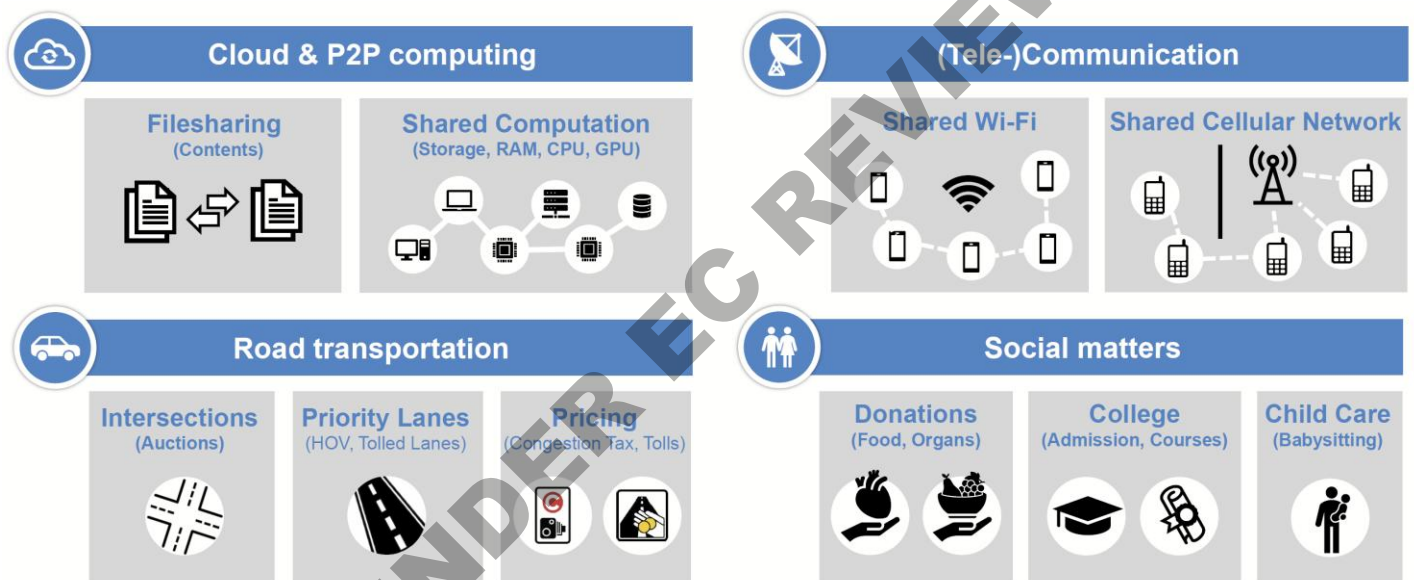


Figure 5: Existing Karma Applications [6].

Important design parameters include the type of currency, parity between currency and resource, balance limits, amount control, initialization, redistribution, transaction rules, payment amount, interaction structure, bidding rules, and the treatment of inactive users. These details matter. If too little Karma circulates, the mechanism may become illiquid, and users may be unable to consume even when urgent. If too much Karma circulates, the incentive to conserve resources weakens. If inactive users accumulate or retain Karma without participating, the system may lose liquidity. If balance limits are too strict, users may be prevented from saving for genuinely high-urgency situations. If they are too loose, hoarding can occur.

For traffic demand management, these mechanism design choices translate into policy choices. A city would need to decide how much Karma each user receives initially, whether Karma expires, whether maximum balances exist, whether unused Karma is redistributed, how prices are calculated, whether prices vary by time and location, how households or fleets are treated, and how to audit transactions. The review therefore provides a design checklist for implementing artificial-currency systems in traffic management.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

3.4.3 KARMA CONGESTION PRICING

The paper "Karma Economies for Sustainable Urban Mobility - A Fair Approach to Public Good Value Pricing" applied the Karma concept to congestion pricing and road access [7]. The work argues that Karma can be used where money faces social limits. In the context of urban mobility, not driving at a congested time can be interpreted as producing or conserving the road-access resource, while driving at that time consumes it. Users earn and spend a resource-specific currency that cannot be bought with money and therefore does not directly depend on income.

The study compared monetary pricing and Karma pricing in a stylized case study based on travel between New Jersey and Manhattan, focusing on route choice when traffic must be redistributed between river crossings. In the case study, a user equilibrium without pricing leads to excessive use of the more attractive but congestion-sensitive route. Both monetary pricing and Karma pricing can move the traffic split toward the system optimum, reducing total travel time. The important difference is distributional. Monetary pricing gives stronger access to users with higher income because their ability to pay is greater. Karma pricing gives access based more directly on urgency because the currency cannot be purchased with external financial resources.

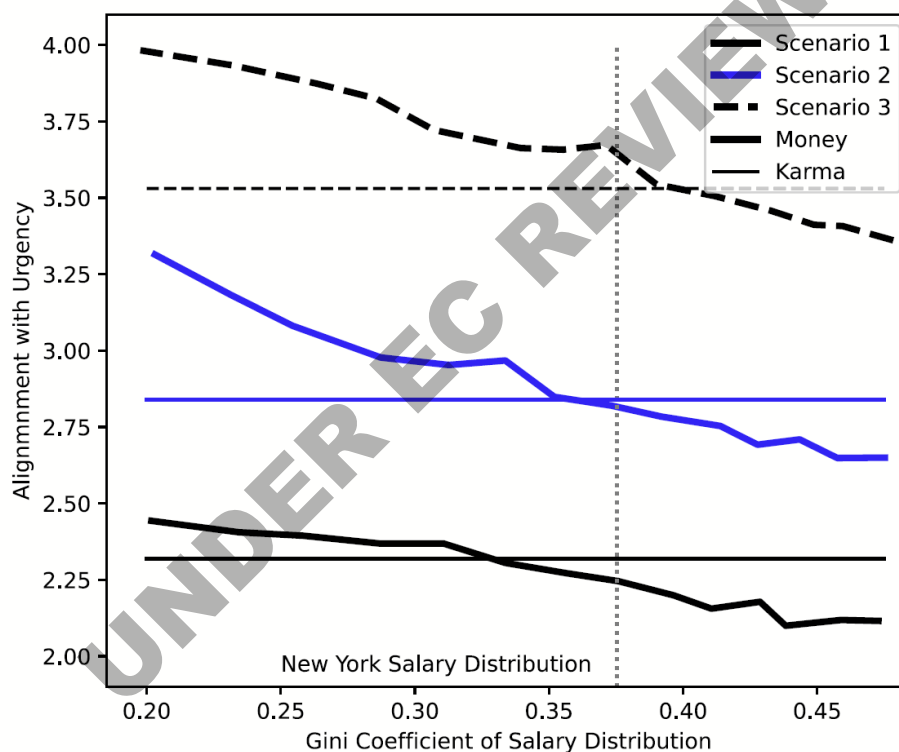


Figure 6: When Karma works better [7]. The superiority of Karma over money in terms of alignment with needs depends on the distribution of salaries. At a certain level of inequality in the income distribution, Karma performs better than money (Gini coefficient above ~ 0.35).

The case-study results show that both mechanisms can reduce average travel time from the unpriced situation by shifting demand to a more efficient route split. The unpriced case produced an average travel time of 45.01 minutes, while both optimized monetary and Karma mechanisms achieved 40.75 minutes in the reported scenario [7]. Total user costs were also reduced compared with the unpriced case. However, the composition of those costs differed. Monetary pricing generated financial fee costs, while Karma did not impose additional monetary fees on users. Karma therefore achieved demand management without adding a direct financial burden.

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The study also identified when Karma is particularly attractive. Karma is most beneficial relative to money when financial power is unequally distributed. In the sensitivity analysis, the advantage of Karma in aligning road access with urgency appears when the income distribution becomes sufficiently unequal, with the case-study threshold around a Gini coefficient of 0.35 as found in our study [7]. This is highly relevant for real cities because income inequality is not an exception; it is a structural feature of many metropolitan areas. In such contexts, monetary congestion pricing may be efficient but politically fragile, while Karma can offer a more acceptable fairness narrative.

3.4.4 RELATIONSHIP TO TRADEABLE CREDIT SCHEMES

Karma and tradeable credit schemes share a common goal: they introduce an artificial mobility budget so that scarce road resources can be allocated without relying only on a conventional toll. The difference is that tradeable credits are exchangeable, while Karma is not. This difference is central to the fairness argument.

Tradeable credits can achieve efficiency by allowing users with higher willingness to pay to purchase additional access rights. They can also compensate users who travel less, because these users can sell unused credits. However, the ability to trade credits may make the system vulnerable to the same income effects as monetary pricing. Users with lower income may sell credits because the money is more urgent than the trip, while users with higher income may buy more credits. The resulting allocation may still be efficient in a monetary sense but may not be aligned with mobility need.

Karma removes the possibility of selling one's mobility rights for money. This can be seen as a limitation from one perspective, because users cannot convert unused travel rights into general purchasing power. From another perspective, it is exactly the source of the fairness benefit: all users must economize the same type of mobility budget over time. The mechanism shifts the basis of choice from ability to pay to the temporal balancing of present and future mobility needs. It does not solve every equity problem, especially where users have permanently different mobility requirements, but it reduces the direct link between road access and income.

For FEDORA, this means that Karma should be treated as a complement to the broader family of traffic demand management instruments. Conventional pricing may be appropriate where equity impacts can be mitigated through revenue redistribution or where public acceptance is already sufficient. Tradeable credits may be appropriate where a cap on total demand is needed, and users accept trading. Karma is promising where public resistance to monetary charges is high and where the policy goal is to allocate scarce spatio-temporal road access according to need rather than purchasing power.

3.4.5 IMPLEMENTATION CONSIDERATIONS

The Karma work also highlights implementation challenges. First, a Karma system requires reliable accounting. The authority must know when users consume the resource and when they refrain from consuming it. This may require sensing infrastructure, digital accounts, secure transaction records, and privacy-preserving governance. Second, the mechanism must be understandable. If users cannot understand how to earn, save, and spend Karma, the mechanism may fail behaviourally even if it is theoretically efficient. Third, the system must maintain liquidity. Amount control, expiry, redistribution, and balance limits are not minor details; they determine whether the mechanism remains usable.

Fourth, the system must address inactive users. If users who rarely travel accumulate Karma indefinitely or if users leave the system with large balances, scarcity signals can become distorted. Fifth, transition periods need attention. A real deployment may involve mixed populations of Karma users and non-users, exemptions, trial periods, or parallel monetary options. Sixth, empirical acceptance remains a crucial next step. Surveys and behavioural experiments are needed to understand whether users perceive Karma as fair, whether they can reason about intertemporal budgets, and how they respond to different user-interface designs.

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These considerations connect directly to FEDORA's smart-city context. Digital traffic management platforms, connected infrastructure, and data spaces can support the sensing, accounting, and simulation capabilities needed for artificial-currency instruments. At the same time, smart-city technology should not be presented as a substitute for public legitimacy. The technology enables implementation; the fairness framework explains and legitimizes it.

3.5 INDIVIDUALIZATION AND MASS CUSTOMIZATION: THE URBAN PRIORITY PASS

3.5.1 FROM NETWORK ACCESS PRICING TO INTERSECTION PRIORITY

The third Task 4.2 objective is to identify means to exploit smart-city technologies for individualization and mass customization of spatio-temporal resource allocation. The Urban Priority Pass [8] addresses this objective by moving beyond traditional area-based congestion pricing toward individual priority at signalized intersections.

Intersections are major bottlenecks in urban traffic networks. Conventional signal control treats users mainly as vehicle flows, queues, or modes. Public transport and emergency vehicles may receive priority, but ordinary users cannot express urgency at intersections. This creates a mismatch. In many other service contexts, priority is available when urgency differs: emergency care uses triage, parcel delivery offers express options, and passenger transport offers reservations. In urban road traffic, however, an urgent taxi trip, delivery, care trip, or time-critical private trip typically receives the same signal treatment as a low-urgency trip, unless it belongs to a predefined priority class.

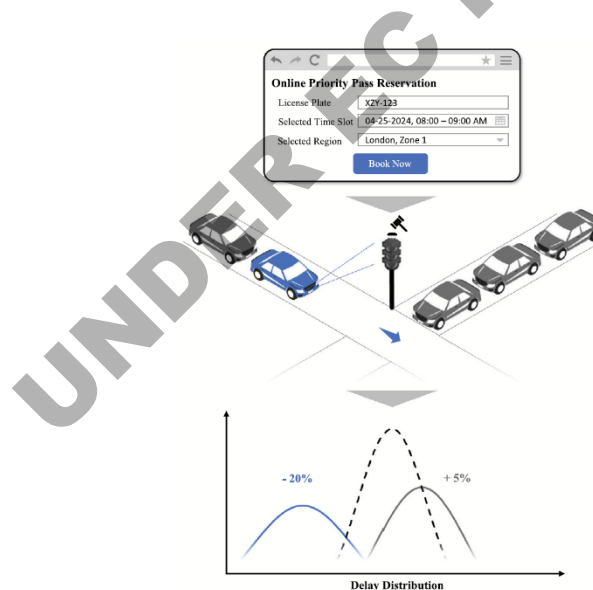


Figure 7: Urban priority pass concept [8].

The Urban Priority Pass proposes a reservation-based economic controller that allows selected vehicles to receive priority at signalized intersections. The concept is particularly relevant for large, congested cities with rich sensor infrastructure. It can support urgent individuals, vulnerable users, taxis, delivery vehicles, emergency vehicles, public transport, or other classes selected by policy. The central idea is not to give unrestricted priority to everyone. Rather, a limited share of vehicles can be entitled to priority during specific time slots or regions, and the signal controller can account for this entitlement when selecting phases.

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3.5.2 CONTROLLER AND ALLOCATION MECHANISM

The Priority Pass controller is based on auction-controlled signalized intersection management [8]. Movement phases compete for the next green phase. Their bid depends on the number of vehicles and the number of entitled vehicles in the movement phase. Two parameters are central. The entitlement share determines how many vehicles in the population possess the Priority Pass. The control threshold determines how strongly the controller prioritizes entitled vehicles relative to ordinary queue pressure. When there are no entitled vehicles, or when the threshold gives no weight to entitlement, the controller behaves similarly to a queue-length-based pressure controller. This is important because it means the Priority Pass can be interpreted as an extension of established actuated control logic rather than a completely separate control paradigm.

Allocation of the Priority Pass can be designed in several ways. A central authority could allocate passes to specific policy-relevant users or vehicle classes. For example, passes could support transit vehicles, emergency services, low-income commuters, vulnerable road users, taxis, delivery vehicles, or specific social and environmental goals. Alternatively, a market could allocate passes to those with the greatest willingness to pay. In a pure monetary market, this raises the same equity concern as congestion pricing. The Priority Pass study therefore also considers redistribution: payments by prioritized users can be redistributed to non-prioritized users or used for public transport and road infrastructure. This makes it possible for prioritized users to reduce their delay while compensating those who may experience small additional delays.

The concept is compatible with several technological implementations. Entitled vehicles could be identified through license plate recognition, digital permits, vehicle-to-infrastructure communication, fleet accounts, or other city-specific infrastructure. The controller does not require fully connected autonomous vehicles, which is important for near-term feasibility. It requires vehicle-identifying infrastructure and some form of pressure or queue information at intersections, both of which are increasingly available in smart-city traffic management systems.

3.5.3 CASE-STUDY EVIDENCE

The Urban Priority Pass was evaluated in a Manhattan-like simulation and then scaled to a Manhattan-sized welfare analysis [4]. The case study shows that prioritizing a limited share of vehicles can reduce delay for entitled vehicles without significantly harming transportation efficiency. The study reports delay reductions up to 40% for entitled vehicles, while preserving network-level performance close to a Max-Pressure-like controller, when applying individual prioritization under the Urban Priority Pass scheme. The analysis of traffic fundamentals indicates that flow and speed reductions relative to the benchmark controller remain small and statistically not meaningful in the tested settings [8].

The welfare analysis is especially relevant for Task 4.2. For a network the size of Manhattan, the study estimates that the Priority Pass could generate large social welfare benefits by reallocating delay reductions toward users with higher urgency. Depending on the urgency scenario, the daily welfare generated was estimated at approximately USD 95.5 million, USD 126.4 million, and USD 158.8 million, with corresponding municipal revenue potentials of approximately USD 0.88 million, USD 1.04 million, and USD 1.34 million per day [8]. These values should be interpreted as proof-of-concept magnitudes under the assumptions of the case study, not as direct deployment forecasts. The qualitative insight is more important: smart-city intersection control can create economic value by allocating delay reductions where they matter most.

The study also finds that a market for priority can systematically benefit users with higher urgency rather than merely users with higher income, especially when redistribution is included. This is a central point for FEDORA. Individual prioritization should not be understood only as a premium service for wealthy drivers. Designed carefully, it can become a mechanism for aligning scarce spatio-temporal mobility resources with social, economic, environmental, or safety needs. Examples include reducing delays for emergency services, improving transit reliability, expediting delivery and taxi fleets to reduce fleet size requirements, protecting vulnerable road users, or supporting users with limited flexibility.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

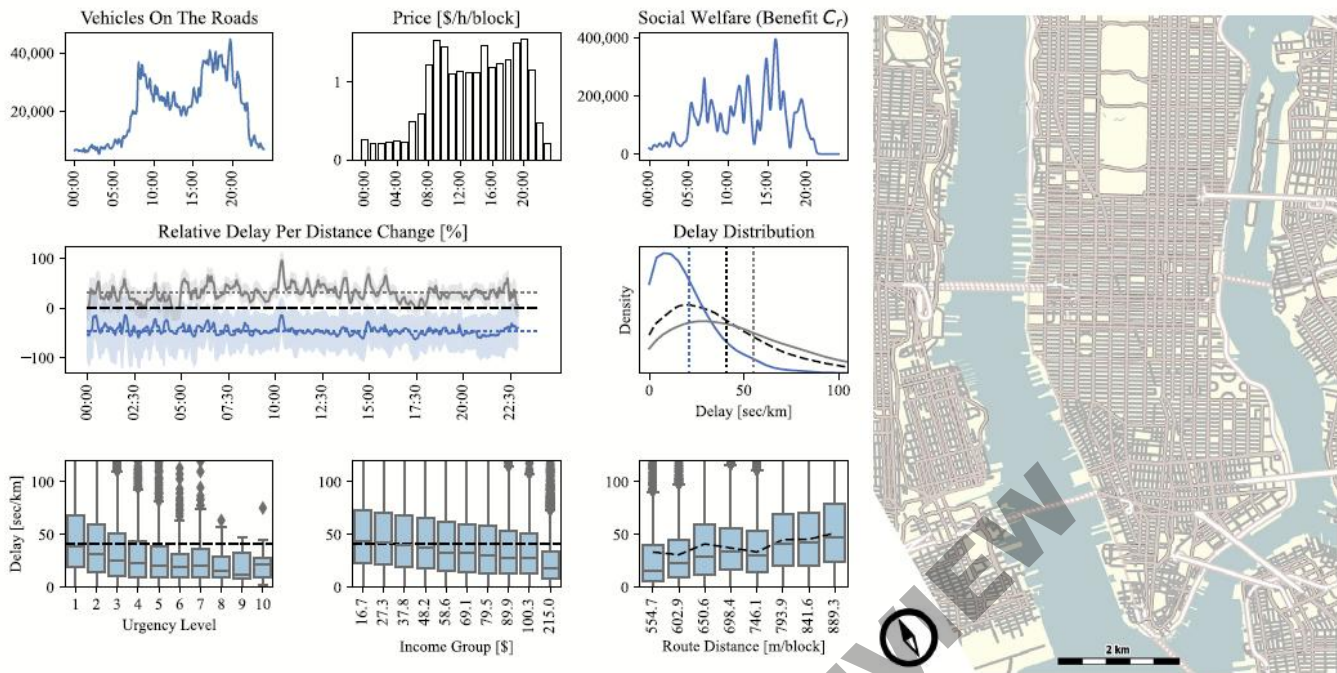


Figure 8: Social welfare analysis of the priority pass for Manhattan [8].

3.6 INTEGRATION INTO FEDORA TRAFFIC MANAGEMENT APPLICATIONS

The work in Task 4.2 contributes to FEDORA by expanding the traffic management toolbox beyond classical optimization. It shows how pricing, artificial currencies, and prioritization can be designed as incentive layers around traffic control systems. This is aligned with the broader WP4 goal of developing optimization and incentivization models for multimodal networks.

The first integration pathway is simulation-based policy design. Before implementing a pricing or priority scheme, candidate mechanisms can be evaluated in a traffic simulation or digital-twin environment. The fairness framework [5] can guide the selection of metrics. For example, a candidate congestion-pricing strategy can be evaluated not only by total travel time and emissions, but also by the distribution of financial costs, delay costs, access, and revenues across income groups, trip purposes, routes, modes, and user classes. Similarly, a Priority Pass controller can be evaluated by average delay, worst-case delay, delay dispersion, impacts on non-entitled users, and welfare by urgency group.

The second integration pathway is incentive-aware control. Social optimum models for signalized intersections and corridors can include weights that reflect user needs, policy priorities, or externally defined fairness considerations. The Priority Pass work [8] provides a concrete example of how an entitlement variable can enter signal control through a modified pressure or auction logic. Karma mechanisms [6, 7] provide a way to define non-monetary budgets that influence user decisions before users enter the network, for example in departure-time or route-choice decisions.

The third integration pathway is public communication and governance. Traffic management algorithms increasingly make automated decisions that affect users. Public authorities therefore need not only performance metrics, but also an explanation of legitimacy. The fairness framework can be used to document why a mechanism was selected, which users are expected to benefit, how burdens are mitigated, and how outcomes will be monitored. This is essential for congestion pricing, where public resistance

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS



can block deployment, and for individual prioritization, where the public may fear preferential treatment if the allocation rules are not transparent.

The fourth integration pathway is smart-city data infrastructure. Karma and Priority Pass systems require timely data on demand, network state, resource consumption, and possibly user entitlements. FEDORA's broader focus on data spaces, sensing, and advanced routing provides the technological environment in which such instruments can be tested. However, data requirements should be proportionate. The Priority Pass was explicitly designed as a near-term concept that does not require universal connected or autonomous vehicles. Karma congestion pricing similarly can be explored initially in simulation or controlled pilots before any city-wide deployment.

3.7 DISCUSSION: EQUITY, ACCEPTANCE, AND LIMITS

The Task 4.2 outputs point to a balanced conclusion. Economic instruments are powerful, but their public acceptability depends on their fairness design. Monetary congestion pricing can reduce congestion and improve efficiency, but it is vulnerable to the criticism that it allocates scarce road resources according to ability to pay. Tradeable credit schemes introduce a mobility budget, but tradability can reintroduce financial-power effects. Karma removes the link to money and can therefore improve fairness in unequal societies, but it requires careful design of liquidity, accounting, and user behaviour. The Urban Priority Pass demonstrates that individualized smart-city priority is technically and economically plausible, but its legitimacy depends on transparent allocation and compensation rules.

This means there is no single universally best instrument. The appropriate mechanism depends on the policy objective, network context, available alternatives, technological infrastructure, and distributional constraints. For a city primarily seeking revenue and congestion relief, monetary pricing with strong redistribution may be suitable. For a city facing strong equity objections, Karma or non-tradeable mobility credits may offer a more acceptable alternative. For corridors or networks with advanced sensing and signal control, individualized priority can create value by differentiating users according to urgency or public policy goals. These instruments can also be combined. A city could implement conventional pricing for area access, Karma budgets for specific peak-period rights, and Priority Pass reservations for time-critical trips or vehicle classes.

A second important conclusion is that fairness should be embedded early. Retrofitting fairness after an efficiency-only design is difficult. Once a price, entitlement rule, or control algorithm is selected, public debate tends to focus on winners and losers. If fairness is included at the design stage, alternative mechanisms can be compared before political positions harden. This is one of the main benefits of the framework developed in [5]: it transforms equity from a vague objection into a structured design dimension.

A third conclusion concerns empirical validation. The published work provides conceptual frameworks, simulation models, software, and case studies. The next step is to test acceptance and behavioural response. Users may not behave as perfectly rational agents. They may misunderstand artificial currencies, distrust data collection, resist perceived restrictions, or respond differently depending on framing. Therefore, future work should include stated-preference surveys, behavioural experiments, pilot studies, and stakeholder engagement. For Karma, the key questions are whether users understand intertemporal mobility budgets and whether they perceive non-tradability as fair. For the Priority Pass, the key questions are willingness to pay, acceptance of priority allocation, and perceived legitimacy of compensation.

3.8 CONCLUSIONS AND NEXT STEPS

Task 4.2 developed a coherent set of dynamic pricing and incentivisation models for traffic management applications. The work addresses one of the main barriers to real-world traffic demand management: public resistance driven by equity concerns. The contribution is not limited to proposing another congestion-pricing variant. Rather, it provides a framework for fairness-aware traffic

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS



engineering, a systematic foundation for non-monetary resource allocation with Karma, a case-study demonstration of Karma-based congestion pricing, and a smart-city concept for individualized intersection priority.

The fairness framework helps traffic engineers and public authorities discuss congestion pricing and related measures in a more objective and systematic way. It identifies fairness-relevant resources, affected actors, transaction types, and quantitative metrics. It also shows that fairness and efficiency do not always need to be in conflict; in many cases, fairer solutions can be found within the set of operationally efficient solutions.

The Karma work shows that artificial currencies can reduce the dependence of traffic demand management on financial ability to pay. Karma congestion pricing can move traffic demand toward system-optimal levels while orienting access more closely toward urgency than income. This is particularly relevant in societies with unequal distributions of financial power, where conventional pricing faces strong fairness objections.

The Urban Priority Pass demonstrates how smart-city sensing and signal control can enable individualized, reservation-based prioritization. By allocating delay reductions to users with higher urgency and compensating others, such mechanisms can increase welfare while preserving traffic efficiency. This opens a path toward mass-customized spatio-temporal road resource allocation.

Future work beyond FEDORA can build on these outputs in multiple directions. First, the fairness framework could be integrated into simulation-based evaluation of pricing and routing strategies. Second, Karma and non-tradeable credit mechanisms can be tested in behavioural experiments and pilot-like digital environments. Third, Priority Pass logic can be connected to existing signal-control and digital-twin tools to assess feasibility under local European network conditions. Fourth, communication material for public authorities can be developed around the fairness framework, emphasizing transparent objectives, distributional impacts, and compensation mechanisms.

Within the context of FEDORA, we continue to explore further novel methodologies for fair traffic control measures. Additionally, to investigate the similarities and differences between Karma economies and tradable credits schemes more systematically, DTU and ETH are working on a joint study (lead: DTU) on the comparison of these two mechanisms in the context of a bottleneck fast lane access problem.

Taken together, Task 4.2 contributes to a more socially feasible generation of traffic management instruments. The core message is that pricing and incentives should not only reduce congestion; they should allocate scarce mobility resources in a way that can be explained, justified, and accepted.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

4 MULTIMODAL HUB OPTIMIZATION FOR TRAFFIC MANAGEMENT

4.1 DEVELOPMENT OF OPTIMISATION ALGORITHM TO OPTIMISE MULTIMODAL HUBS

This section presents the FEDORA algorithmic solution for multimodal-hub planning, covering its state-of-the-art foundations, architecture, data requirements, mathematical formulation, software implementation and sensitivity-based validation.

The solution selects or upgrades candidate multimodal-hub locations, determines the modes and service units available at each location, activates feasible modal links and accommodates the complete origin-destination (OD) demand. The study area is represented by urban clusters, with candidate hubs pre-screened according to available space, compatibility with existing services, accessibility and electrical capacity. Parallel directed links between the urban clusters may represent the presence of UAV, bus, bicycle and scooter services, each with its own travel time, operating cost and throughput capacity.

The system-oriented Mixed Integer Linear Programming (MILP) minimises a normalised weighted composite cost function subject to area, charging-power, hub-throughput and link-capacity constraints. Binary variables represent hub, mode and link decisions; integer variables represent infrastructure units; and continuous variables represent OD flows. The number of derived hubs emerges from demand, network topology, existing assets, resource limits and the selected objective weights. Each scenario therefore supplies candidate hubs, infrastructure and site resources, modal links, travel times, costs, capacities and an OD matrix. The model determines:

1. which candidate clusters are selected as hubs and which existing locations are upgraded,
2. which modes are available at each hub and how many existing and additional service units are used,
3. which directed mode-specific links are activated, including parallel modal links between the same clusters,
4. how the complete OD demand is allocated to direct or multi-hub paths, including intermodal transfers,
5. whether area, charging-power, hub-service and link-capacity limits are respected,
6. which strategic outputs are transferred to the FEDORA journey-planning and simulation platform.

A location is selected only when required for feasibility or when its system-wide benefit justifies its activation and infrastructure costs. The Python/Gurobi implementation is driven by external JSON scenarios, aligned with the MTM spaces defined in T2.3 and the WP3 Data Space Service, including data from MobiDataLab (AKKIS) and the Cyprus National Access Point. It validates inputs, solves the model, exports hubs, infrastructure, links, OD-mode-link flows and KPIs, and generates SUMO-oriented TAZ, OD-relation and hub point-of-interest files. This deliverable uses synthetic study areas; the final validation will use the Nicosia in-silico pilot.

4.1.1 STATE OF THE ART AND BACKGROUND

Cities seek to reduce dependence on private cars by strengthening public transport, cycling and emerging mobility services, yet car use remains high, particularly for peri-urban trips to city centres. The November 2023 MobiDataLab hackathon, organised with Leuven's public transport authority and coordinated by Akkodis, addressed this challenge by seeking optimal locations and services for multimodal hubs [9]. Existing approaches and findings from this initiative provide valuable insights into the design of multimodal mobility hubs.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Specifically, Xanthopoulos et al. [10] propose an optimisation framework that considers both hub disposition and capacity. It combines modules for estimating demand at potential hubs, optimising shared-vehicle capacity and availability at hub level, and identifying the optimal hub configuration. PosadMaxwan [11] scores potential hubs using proximity to points of interest and transport stops, population density and related indicators. The highest-scoring hub is selected, its covered area is calculated, and the procedure is repeated until the area is served. Urbsim tool [12], developed for London, examines the extent to which one transport stop interacts with other stops and surrounding urban activities. The OptimalHubPlacement algorithm [13], the winning solution of the MobiDataLab Codagon Challenge, provides a prototype for data-driven hub-placement analysis. Specifically, the proposed algorithm adopts a system-optimal perspective, minimising weighted network-wide cost rather than individual traveller cost. This supports strategic comparison of travel benefits, investment needs and service feasibility under alternative policy priorities.

Existing approaches are largely prototypical and dependent on local data structures, which limits transferability. FEDORA advances the state of the art by combining multimodal hub selection, infrastructure sizing, modal-link activation, complete origin–destination (OD) flow allocation, and the integration of Unmanned Aerial Vehicles (UAVs) as an additional transport mode within a single capacity-constrained MILP framework. This enables the optimization of conventional transport modes alongside UAV-based mobility and logistics services, extending the applicability of multimodal transport systems. Reusable technologies, externally defined scenarios and harmonised Data Space access improve portability, while explicit physical constraints, reuse of existing assets, ETH incentive inputs and direct interfaces to journey planning and SUMO/TraCI support end-to-end evaluation and feedback from realised operational indicators.

4.1.2 SOLUTION DESIGN AND ARCHITECTURE

The solution comprises two connected layers. The strategic layer uses a cluster-based MILP to select or upgrade hubs, size modal infrastructure, activate mode-specific links and route the complete OD demand. The operational layer translates selected UAV hubs and aerial links into scheduled, cyclic or demand-responsive services evaluated jointly with ground traffic.

At macroscopic level, each urban cluster represents an aggregated demand zone, such as a residential district, employment centre, interchange, campus, logistics site or hospital. The OD matrix records passenger or parcel movements over a fixed planning horizon. Only clusters satisfying basic requirements for area, service integration and charging power are retained as candidate hubs.

Clusters are connected by separate directed links for each feasible mode. Several modes may serve the same cluster pair, each with its own travel time, cost and capacity. The model activates the required links and routes for every OD demand from origin to destination, directly or through intermediate hubs.

Section 4.1 outputs selected hubs, installed capacity, active links and aggregate OD-mode-link flows. Section 4.2 uses these outputs to construct door-to-door journeys, while Section 4.3 operationalises the UAV services in simulation. Realised travel times, costs and capacities can then update subsequent optimisation runs.

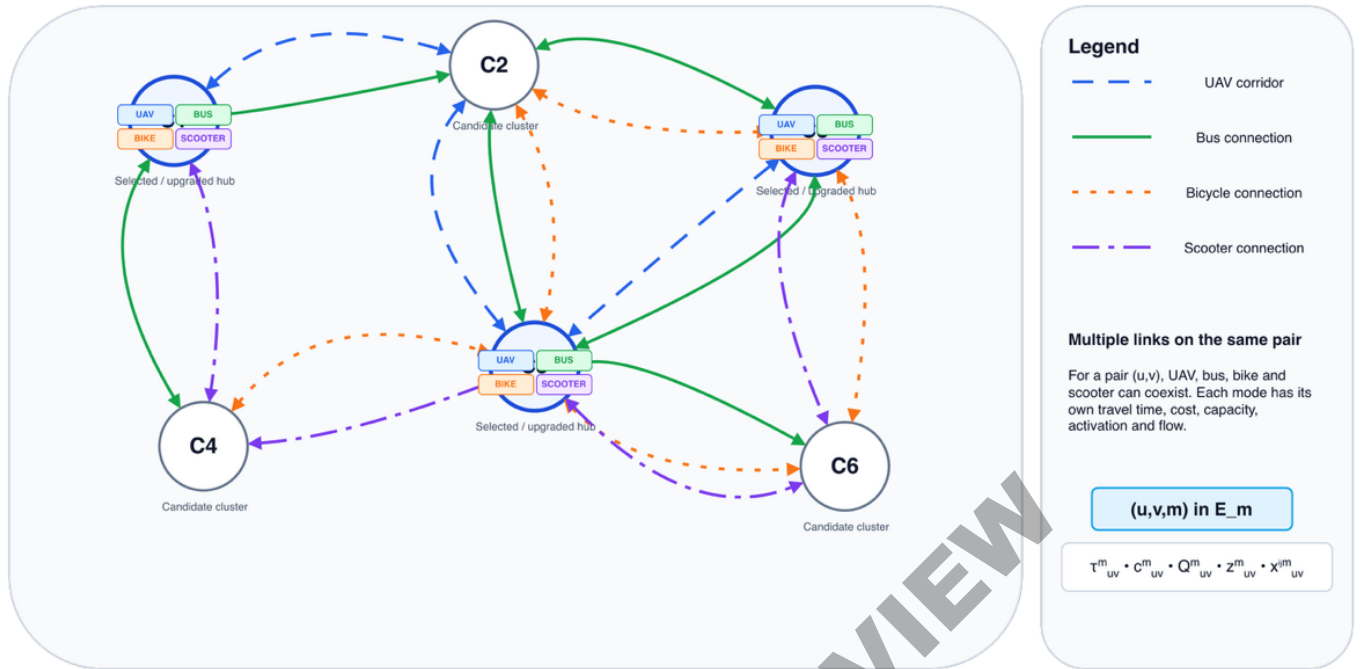


Figure 9: Cluster-based multimodal hub network with multiple mode-specific links between cluster pairs.

4.1.3 DEVELOPMENT OF OPTIMISATION ALGORITHM TO OPTIMISE MULTIMODAL HUBS

4.1.3.1 SELECTION AND UPGRADING

Selection determines whether a candidate hub location joins the multimodal network; upgrading determines the additional infrastructure required after existing assets are accounted for.

Selection is the binary decision variable, y_k , used to activate candidate location k as a multimodal hub:

$$y_k = \begin{cases} 1, & \text{if candidate cluster } k \text{ is selected as a hub,} \\ 0, & \text{otherwise.} \end{cases}$$

Upgrading is the integer decision to install additional service units at a selected hub. Let N_{km}^0 denoting the number of service units of mode m already available at candidate hub k , and let Δn_{km} denoting the number of additional units installed by the model. The total infrastructure n_{km} , of mode m already available at candidate hub k is:

$$n_{km} = N_{km}^0 y_k + \Delta n_{km}.$$

Existing assets contribute capacity without being charged as new installations; costs apply only to additional units selected by the model.

4.1.3.2 CLUSTER-BASED MULTIMODAL NETWORK

Selected locations form a directed multimodal graph (Figure 9). A cluster may be an OD zone, a candidate hub or both, and each mode has its own set of feasible directed links. Thus, the same ordered cluster pair may support several independently activated services, each with distinct time, cost and capacity.

PU - PUBLIC

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Mode-specific links connect pre-screened hubs. A finer representation can add explicit access and egress links for origin-only or destination-only zones without changing the core flow formulation. Intermodal transfers are allowed when the required services and capacities are available, enabling direct and multi-hub paths.

4.1.3.3 MODAL SERVICE UNITS AND CAPACITY INTERPRETATION

Each active hub is assigned an integer number of mode-specific service units:

- UAV: one landing/take-off pad equipped with charging infrastructure,
- Bus: one bus bay equipped with charging infrastructure (assuming electric bus),
- Bicycle: one bicycle dock or bicycle service position,
- Scooter: one scooter dock with interchangeable-battery support and no on-site charging requirement.

Capacity is represented at two levels: vehicle occupancy limits one trip, whereas service-unit capacity measures the passenger-handling events supported by repeated operations over the planning horizon. Vehicle occupancy and service-unit capacity are different quantities. Vehicle occupancy is the maximum number of passengers carried by one vehicle trip. The MILP parameter μ_m is the aggregate number of passenger-handling events that one installed service unit (mode m) can process during the planning horizon. It is derived from

$$\mu_m = Occ_m Cyc_m,$$

where Occ_m is the maximum passenger occupancy per trip and Cyc_m is the number of vehicle-handling cycles supported by one service unit of mode m during the horizon. Table 2 gives indicative one-hour values. UAV taxis carry at most two passengers per flight, while bicycles and scooters serve one passenger per trip; service-unit capacities account for repeated operations during the hour.

Table 2: Indicative service-unit capacities

Mode	Maximum occupancy per vehicle trip	Service events per unit per hour	Representative
UAV taxi	2 passengers	8 pad-handling events	16 passenger-handling events/hour/pad
Electric bus	40 passengers	4 bay-handling events	160 passenger-handling events/hour/bay
Bicycle	1 passenger	6 check-out/return events	6 passenger-handling events/hour/dock
Scooter	1 passenger	6 check-out/return events	6 passenger-handling events/hour/dock

The link-capacity parameter Q_{uv}^m , capacity on the link for mode m with link connecting clusters u and v , is also an aggregate throughput over the planning horizon. For example, a UAV corridor may accommodate several UAV flights within one hour even though each individual UAV flight carries at most two passengers.

4.1.3.4 ASSUMPTIONS

The formulation preserves linearity and is based on the following assumptions:

1. OD demand, modal travel times and operating costs are deterministic within each scenario,
2. flow variables are continuous, allowing an OD demand to be split across feasible paths or modes,
3. all OD demand must be served with unmet demand not permitted in the core formulation,
4. infrastructure sizes are integer decisions,
5. available area is specified in square metres and charging power in kW,
6. only UAV pads and electric bus bays consume on-site charging power in the current model,
7. no separate per-trip energy-budget constraint is imposed,
8. mode-specific link capacities and hub service-unit capacities are defined over the same planning horizon,
9. the selected network must be connected through active incident links, but a fixed number of hubs is not imposed.

The MILP therefore produces a complete network, infrastructure and OD-flow solution. Time-dependent demand, detailed schedules, headways, indivisible groups and restricted-airspace routing are addressed through sensitivity analysis or operational simulation.

As a future extension, full OD demand satisfaction may be relaxed from a hard to a soft constraint, allowing unmet demand to be penalised rather than rendering capacity-constrained scenarios infeasible. This will enable the model to quantify potential capacity shortfalls while still providing feasible planning solutions.

4.1.3.5 FORMAL MILP FORMULATION

The formulation follows the planning sequence described above.

SETS AND INDICES

The sets distinguish urban clusters, candidate hubs, transport modes, feasible directed links by mode and positive-demand OD pairs. Separate modal link sets permit parallel services between the same clusters.

Table 3: Sets and indices

Symbol	Definition
C	set of urban clusters, indexed by i, j, k, q, u, v
$H \subseteq C$	set of pre-screened candidate hub clusters
M	set of transport modes {UAV,bus,bike,scooter}
$E_m \subseteq H \times H$	set of feasible directed links for mode m
$\mathcal{D}$	set of OD pairs (i, j) with $D_{ij} > 0$ and $i \neq j$

PARAMETERS

Scenario parameters describe OD demand, modal times and costs, existing and maximum infrastructure, activation and installation costs, site area and charging power, and service-unit and link throughput. They remain fixed within each solve.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Table 4: Parameters

Symbol	Unit	Definition
D_{ij}	passengers/horizon	OD demand from cluster i to cluster j
τ_{uv}^m	min/passenger	aggregate travel time on link (u, v) by mode m
c_{uv}^m	monetary unit/passenger	operating or generalised cost on modal link (u, v)
Q_{uv}^m	passengers/horizon	capacity of modal link (u, v)
F_k	monetary unit	fixed cost of selecting/upgrading candidate hub k
G_{km}	monetary unit/unit	installation cost of one new service unit of mode m at k
A_k	m^2	available area at candidate hub k
P_k	kW	available charging-power capacity at candidate hub k
a_m	m^2/unit	area required by one service unit of mode m
p_m	kW/unit	charging power required by one service unit of mode m
μ_m	handling events/horizon/unit	service capacity of one infrastructure unit of mode m
N_{km}^0	units	existing service units of mode m at candidate hub k
$\bar{N}_{km}$	units	maximum service units of mode m allowed at hub k
S_T, S_C, S_F, S_I	positive scales	objective normalisation factors
$\omega_T, \omega_C, \omega_F, \omega_I$	dimensionless	objective-component weights

For modes that do not use on-site charging in the current configuration,

$$p_{bike} = p_{scooter} = 0.$$

DECISION VARIABLES

Table 5 lists the decision variables in planning order.

Table 5: Decision variables

Symbol	Type	Definition
y_k	binary	1 if candidate hub k is selected/upgraded
w_{km}	binary	1 if mode m is available at hub k
n_{km}	non-negative integer	total service units of mode m at hub k
Δn_{km}	non-negative integer	additional service units installed at hub k
z_{uv}^m	binary	1 if modal link (u, v) is activated for mode m
x_{ijm}^{ijm}	non-negative continuous	OD flow (i, j) using modal link (u, v, m)

OBJECTIVE FUNCTION

The model minimises the normalised generalised system cost of passenger travel, service operation and infrastructure development:

$$\min \quad \omega_T \frac{\sum_{(i,j) \in \mathcal{D}} \sum_{m \in M} \sum_{(u,v) \in E_m} \tau_{uv}^m x_{uv}^{ijm}}{S_T} + \omega_C \frac{\sum_{(i,j) \in \mathcal{D}} \sum_{m \in M} \sum_{(u,v) \in E_m} c_{uv}^m x_{uv}^{ijm}}{S_C} + \omega_F \frac{\sum_{k \in H} F_k y_k}{S_F} + \omega_I \frac{\sum_{k \in H} \sum_{m \in M} G_{km} \Delta n_{km}}{S_I}.$$

The four terms represent passenger travel time, modal operating cost, fixed hub cost and additional infrastructure cost. Normalisation makes them comparable, while scenario weights express planning priorities and encourage reuse of existing assets were beneficial.

FLOW CONSERVATION AND FULL DEMAND SATISFACTION

For every positive OD pair, flow balance is imposed at each cluster:

At the origin cluster i ,

$$\sum_{m \in M} \sum_{(i,v) \in E_m} x_{iv}^{ijm} - \sum_{m \in M} \sum_{(u,i) \in E_m} x_{ui}^{ijm} = D_{ij}.$$

At the destination cluster j ,

$$\sum_{m \in M} \sum_{(j,v) \in E_m} x_{jv}^{ijm} - \sum_{m \in M} \sum_{(u,j) \in E_m} x_{uj}^{ijm} = -D_{ij}.$$

At every intermediate cluster q , where $q \neq i$ and $q \neq j$

$$\sum_{m \in M} \sum_{(q,v) \in E_m} x_{qv}^{ijm} - \sum_{m \in M} \sum_{(u,q) \in E_m} x_{uq}^{ijm} = 0.$$

At the origin, the complete OD quantity is injected into the network. At the destination, the same quantity is removed from the network balance. At every intermediate cluster, total incoming and outgoing flow are equal. Flow may transfer from one mode to another at a selected hub, but it cannot be created, lost or retained there. These equations are therefore the mechanism that guarantees full demand service.

FLOW ONLY ON ACTIVATED LINKS

$$x_{uv}^{ijm} \leq D_{ij} z_{uv}^m, \quad \forall (i,j) \in \mathcal{D}, m \in M, (u,v) \in E_m.$$

If $z_{uv}^m = 0$, then $x_{uv}^{ijm} = 0$ for every OD pair. Positive flow therefore requires the corresponding modal link to be activated.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

MODAL AVAILABILITY AT BOTH ENDPOINTS

$$z_{uv}^m \leq w_{um}, \quad z_{uv}^m \leq w_{vm}, \quad \forall m \in M, (u, v) \in E_m.$$

Activating a modal connection also requires the relevant service to exist at both ends. For example, an UAV link can be used only when UAV infrastructure is available at both its departure and arrival hubs.

MODE AVAILABILITY ONLY AT SELECTED HUBS

$$w_{km} \leq y_k, \quad \forall k \in H, m \in M.$$

A mode can be available only at a selected hub; therefore, unselected locations cannot offer services or support active links.

EXISTING INFRASTRUCTURE AND ADDITIONAL INSTALLATION

$$n_{km} = N_{km}^0 y_k + \Delta n_{km}, \quad \forall k \in H, m \in M,$$

$$n_{km} \leq \bar{N}_{km} w_{km}, \quad \forall k \in H, m \in M,$$

$$n_{km} \geq w_{km}, \quad \forall k \in H, m \in M.$$

These equations connect the strategic selection decision to the physical infrastructure plan. The equality combines existing and newly installed units, while the inequalities enforce technical upper bounds, prevent installation when a mode is unavailable and require at least one unit whenever a service is offered.

AVAILABLE AREA

$$\sum_{m \in M} a_m n_{km} \leq A_k y_k, \quad \forall k \in H.$$

The installed infrastructure must fit within the available site area measured in square metres. If $y_k = 0$, the right-hand side is zero and no units can be installed.

AVAILABLE CHARGING POWER

$$\sum_{m \in M} p_m n_{km} \leq P_k y_k, \quad \forall k \in H.$$

Charging-dependent infrastructure is also limited by the electrical capacity available at the location. In the present configuration, UAV pads and electric bus bays consume charging power, whereas bicycle docks and scooter docks have zero on-site charging-power requirement; scooters are supported through interchangeable batteries.

HUB MODAL SERVICE CAPACITY

Define the passenger-handling flow of mode m at hub k as all incoming and outgoing OD flow using that mode. The capacity constraint is

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

$$\sum_{(i,j) \in \mathcal{D}} \left(\sum_{(k,v) \in E_m} x_{kv}^{ijm} + \sum_{(u,k) \in E_m} x_{uk}^{ijm} \right) \leq \mu_m n_{km}, \quad \forall k \in H, m \in M.$$

Processed service events cannot exceed the throughput provided by the installed units.

MODE-SPECIFIC LINK CAPACITY

$$\sum_{(i,j) \in \mathcal{D}} x_{uv}^{ijm} \leq Q_{uv}^m z_{uv}^m, \quad \forall m \in M, (u,v) \in E_m.$$

The left-hand side aggregates every OD flow assigned to the same modal link. If the link is inactive, the right-hand side is zero. If active, the total assigned flow cannot exceed Q_{uv}^m .

CONNECTIVITY OF SELECTED HUBS

$$\sum_{m \in M} \left(\sum_{(k,v) \in E_m} z_{kv}^m + \sum_{(u,k) \in E_m} z_{uk}^m \right) \geq y_k, \quad \forall k \in H.$$

Each selected hub must have at least one active incident link, preventing isolated locations from being funded.

VARIABLE DOMAINS

$$\begin{aligned} y_k, w_{km}, z_{uv}^m &\in \{0,1\}, \\ n_{km}, \Delta n_{km} &\in \{0,1,2, \dots\}, \\ x_{uv}^{ijm} &\geq 0. \end{aligned}$$

4.1.3.6 EXECUTABLE PYTHON/GUROBI IMPLEMENTATION

The MILP is implemented as a transferable Python/Gurobi workflow in which model logic is separated from external scenario data.

SCENARIO INPUT

Each JSON scenario maps directly to the formulation and specifies clusters, candidate hubs, modes, OD demand, directed links, times, costs, capacities, infrastructure, site resources, objective weights and normalisation values. Exact duplicate links are removed, while conflicting definitions are reported as errors.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS



MODEL EXECUTION

After validation, the executable:

1. loads and validates the JSON scenario,
2. constructs the Gurobi decision variables,
3. creates the normalised objective,
4. adds flow, activation, infrastructure, area, power and capacity constraints,
5. solves the MILP using the specified time limit and relative MIP gap,
6. writes optimisation outputs,
7. writes SUMO-oriented TAZ, OD and selected-hub files.

Execution requires Python, `gurobipy` and a valid Gurobi licence; the active environment must reference the corresponding installation and licence.

4.1.3.7 TRANSLATION OF OPTIMISATION OUTPUTS TO SUMO

Because the MILP operates at cluster level and SUMO uses zones, edges, persons and vehicles, the export stage maps the strategic solution to simulation inputs while preserving OD quantities, selected hubs and modal structure. Specifically,

- Clusters are exported as SUMO Traffic Assignment Zones (TAZ) with source and sink edges.
- The OD matrix is exported as TAZ-to-TAZ relations for trip and route generation.
- Selected hubs are exported as transfer locations or points of interest.
- Bus, bicycle and scooter services are represented through public-transport, micromobility or person-trip definitions.
- UAV links are represented as virtual inter-hub connections or through an external Python/TraCI module synchronised with SUMO.
- Simulation returns realised times, delays, queues and utilisation for subsequent recalibration.

4.1.3.8 SOFTWARE IMPLEMENTATION AND INTERFACES TO THE FEDORA SIMULATION PLATFORM

The interface exchanges validated JSON inputs and optimisation outputs with the FEDORA platform. Strategic hub, link and flow decisions are exported to journey planning and SUMO/TraCI, while operational KPIs are returned for validation and scenario refinement. Separating model logic from data supports base cases and sensitivity studies without source-code changes.

4.1.3.9 RESULTS

A factorial sensitivity analysis combined three OD-demand levels with three normalised objective-weight profiles, producing nine runs. Every run served the complete demand while satisfying link, hub, area and charging-power constraints.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

SCENARIO DESIGN

The reference matrix contains 760 trips. Low and high cases scale each OD entry by 0.75 and 1.25. The three weight profiles vary the emphasis on travel time, operating cost, fixed hubs and additional infrastructure (Table 6); all weights of the objective S_T , S_C , S_F , S_I representing travel Time, operating Cost, Fixed hub cost and Installation cost, respectively are dimensionless weights and sum to one (Table 7).

Table 6: Demand scenarios used in the sensitivity analysis

Demand level	Multiplier	Total OD demand
Low	0.75	570
Reference	1.00	760
High	1.25	950

Table 7: Normalised objective-weighted profiles for objective function

Profile	Travel time (S_T)	Operating cost (S_C)	Fixed hubs (S_F)	Installation (S_I)
Balanced	0.40	0.25	0.15	0.20
Time priority	0.70	0.15	0.05	0.10
Cost/infrastructure priority	0.15	0.20	0.30	0.35

COMPARATIVE RESULTS

Because each weight profile represents a different planning priority,



Table 8 compares physical KPIs rather than normalised objective values: average passenger time, operating cost per passenger and selected or upgraded hubs.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Table 8: Core performance indicators for the nine illustrative scenarios

Demand	Objective profile	Total demand	Avg. time (min/pass.)	Operating cost (per pass.)	Selected hubs
Low	Balanced	570	21.10	1.51	11
Low	Time priority	570	11.26	5.08	10
Low	Cost/infrastr. priority	570	25.53	0.72	10
Reference	Balanced	760	21.67	1.37	11
Reference	Time priority	760	12.24	4.80	11
Reference	Cost/infrastr. priority	760	25.76	0.71	10
High	Balanced	950	22.25	1.24	11
High	Time priority	950	14.07	4.14	12
High	Cost/infrastr. priority	950	25.63	0.71	10
Reference Demand					
Balanced 21.67 min/passenger 1.37 cost units/passenger 11 selected hubs		Time priority 12.24 min/passenger 43.5% lower travel time (from balanced) 4.80 cost units/passenger		Cost/infrastructure priority 0.71 cost units/passenger 48.0% lower operating cost (from balance) 25.76 min/passenger	

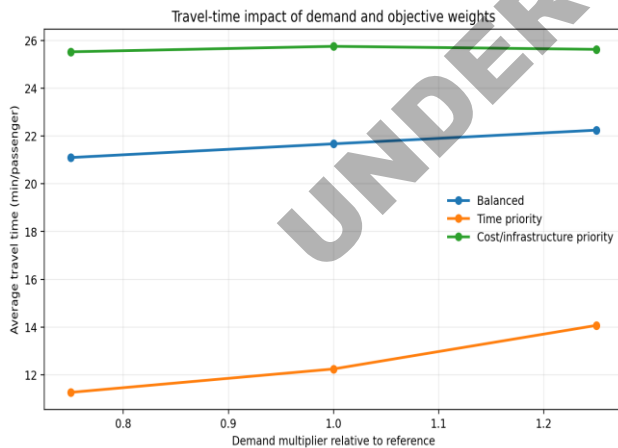


Figure 10: Average travel time under demand and objective-weight variations.

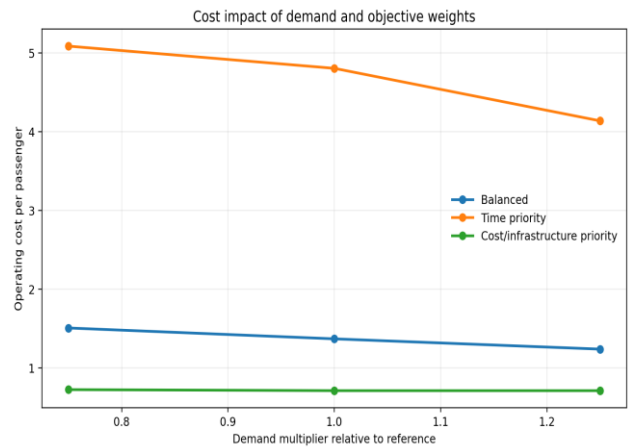


Figure 11: Operating cost per passenger under demand and objective-weight variations

At reference demand, the time-priority profile reduced average travel time (Figure 10) from 21.67 to 12.24 min/passenger (43.5%) but increased operating cost (Figure 11) from 1.37 to 4.80 units/passenger through greater UAV use and additional UAV infrastructure. This demonstrates the trade-off between time savings and faster-mode costs.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

Conversely, the cost/infrastructure-priority profile reduced operating cost to 0.71 units/passenger (48.0% below the balanced case), selected ten hubs (Figure 12), avoided additional UAV units and relied mainly on micromobility. Average travel time increased to 25.76 min/passenger (18.8% above balanced).

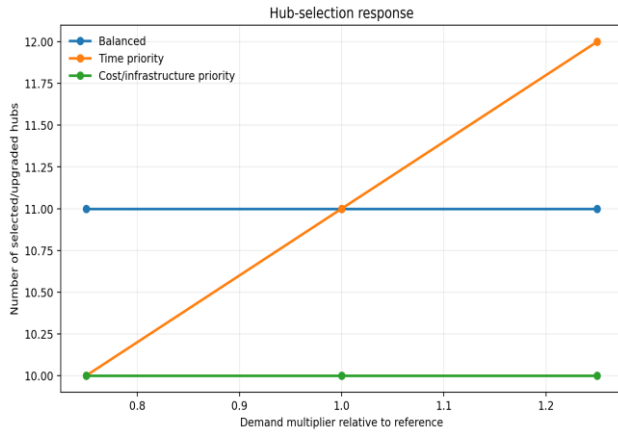


Figure 12: Number of selected of upgraded hubs.

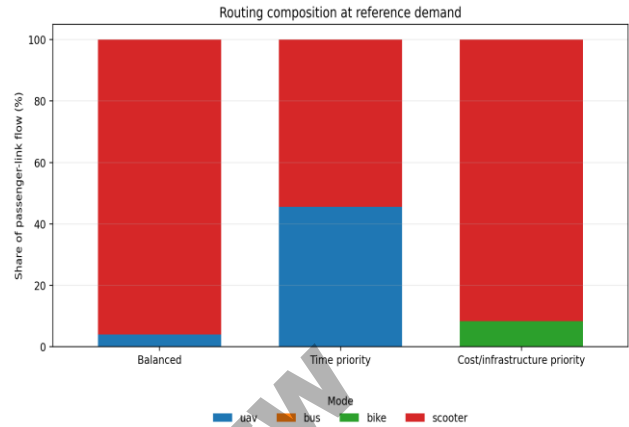


Figure 13: Passenger-link flow composition at reference demand.

Under balanced weights, eleven hubs were retained and average travel time rose by about 5.4% from low to high demand. Under time-priority weights, the network expanded from ten to twelve hubs, showing that higher demand can justify additional hubs when travel-time reduction is valued strongly.

Figure 13 reports link-flow shares, not unique-passenger modal shares: a passenger contributes to every traversed link. The time-priority profile uses substantial UAV flow, whereas the balanced and cost-priority profiles rely mainly on scooters, with limited bicycle and bus use in this synthetic example.

4.2 DEVELOPMENT OF AN UAV PATH PLANNING MODEL

Section 4.3 converts the UAV-enabled hubs, aerial links, aggregate demand and pad capacity selected in Section 4.1 into individual trajectories, requests, queues and repeated service cycles synchronised with the SUMO ground network.

4.2.1 OBJECTIVE AND SCOPE

The UAV component tests whether strategically selected aerial services are operationally feasible under explicit vehicle, route and timing conditions. Capacity-constrained UAVs carry passengers or parcels, follow compatible routes, operate on schedules or in response to demand, and record interactions with ground access, egress and traffic conditions. It supports passenger UAV taxi services, parcel-delivery services, hub-to-hub movements, hub-to-special-location movements, scheduled and cyclic operations that are repeated during the simulation horizon, demand-responsive assignment of queued requests, and collection of traffic data from the UAV field of view.

Figure 14 presents the UAV path-planning and operational framework developed within FEDORA. For each mission, the module verifies vehicle-capacity constraints, generates the shortest direct flight path, updates the UAV operational state, and manages repeated service cycles and queued requests throughout the simulation horizon. In parallel, UAVs collect traffic information through

their field of view (FoV), enabling the extraction of traffic indicators that support monitoring, operational evaluation, and feedback to the FEDORA simulation platform.

The demonstrator uses direct Euclidean paths plus take-off, landing and service times. This is sufficient to assess feasibility, timing, queues and multimodal travel effects, while the architecture can later incorporate waypoint networks, no-fly zones, altitude layers, weather and conflict-resolution rules.

The following subsections describe service locations and requests, capacity checks, path generation, state updates, repeated operations, queue management, data exchange, field-of-view observations and validation.

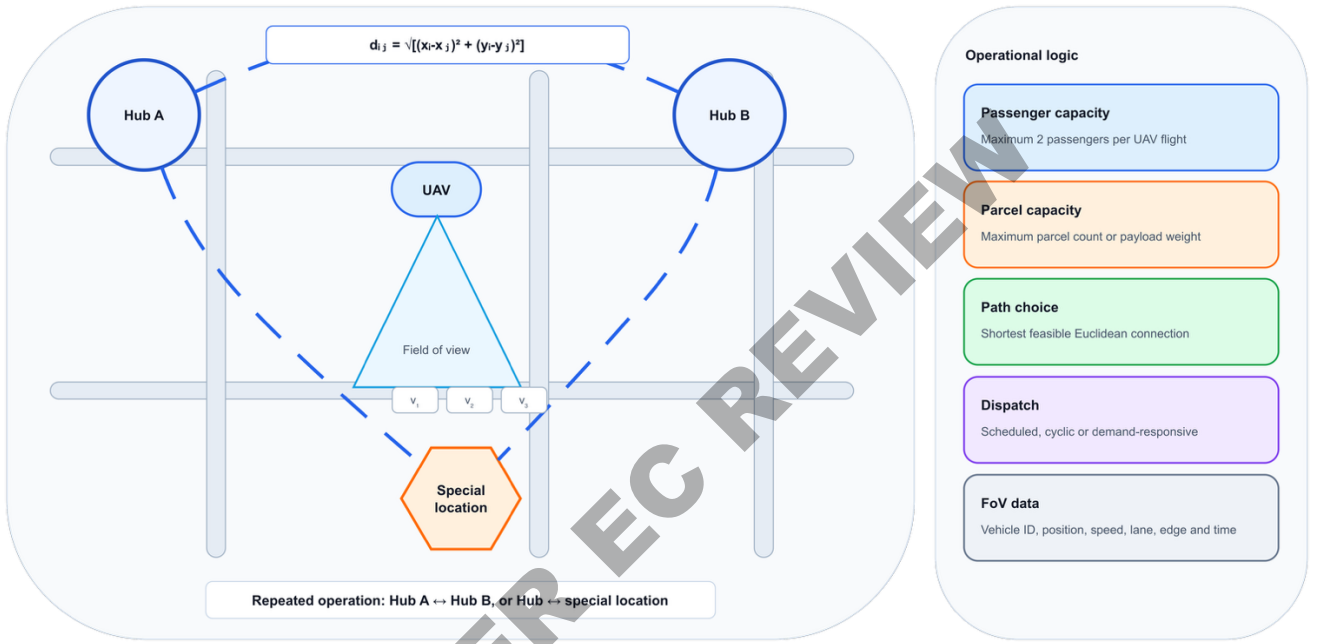


Figure 14: UAV path planning, repeated services and field-of-view monitoring.

4.2.2 UAV-COMPATIBLE LOCATIONS AND SERVICE DEFINITIONS

The operational model combines UAV-enabled hubs selected in Section 4.1 with predefined strategic destinations to form the service nodes for passenger, parcel and monitoring missions.

Let L denote the set of UAV-compatible service locations. A location may be a UAV-enabled multimodal hub selected by the optimisation model, an existing vertiport or landing site, a university campus, a hospital or emergency-service location, a logistics depot or parcel-delivery point, or another predefined strategic destination.

Each location $\ell \in L$ is represented by planar coordinates

$$\mathbf{p}_\ell = (x_\ell, y_\ell).$$

Each service is defined by origin, destination, type and dispatch rule. The type distinguishes passenger, parcel and monitoring missions; the rule specifies fixed, cyclic or demand-responsive dispatch.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

The following service patterns are represented:

- hub-to-hub: repeated or requested movement between two UAV-enabled hubs,
- hub-to-special-location: movement between a selected hub and a predefined external destination,

4.2.3 UAV AND REQUEST CAPACITY

Requests are assigned only when a compatible UAV has sufficient capacity. Individual passenger, parcel and payload limits are distinct from the aggregate pad throughput used in Section 4.1.

Let U be the UAV fleet. Each UAV $u \in U$ is characterised by passenger capacity, parcel-count capacity, optional payload-weight capacity, cruise speed v , take-off, landing and service times, and current position, state, destination and remaining range or operating-time allowance.

Passenger and parcel missions may use different UAV classes, with capacity constraints selected by service type. This preserves the distinction between individual vehicle capacity and strategic pad throughput.

4.2.4 EUCLIDEAN SHORTEST-DISTANCE PATH PLANNING

For each compatible vehicle-request pair, the path generator computes the direct aerial segment. Its distance determines nominal flight time and supports comparison among feasible assignments.

For compatible locations $i, j \in L$, the direct Euclidean distance is

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}.$$

The nominal flight time of UAV u is

$$t_{uij}^{flight} = \frac{d_{ij}}{v_u}.$$

The complete service time includes take-off, flight, landing and passenger/parcel handling:

$$t_{uij}^{service} = t_u^{takeoff} + t_{uij}^{flight} + t_u^{landing} + t_{uij}^{handling}.$$

Fixed-destination requests use the direct origin-destination segment. When several requests are feasible, dispatch may also consider waiting time, service priority and repositioning distance.

The direct Euclidean model is appropriate for the current operational demonstrator, as drone connections are pre-planned and their flight feasibility will be assessed considering relevant physical and regulatory constraints. If obstacles or restricted airspace are introduced, L can be expanded into a waypoint graph and the shortest feasible path can be computed over permitted aerial segments.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

4.2.5 UAV MOVEMENT AND STATE UPDATE

Each UAV follows explicit waiting, loading, take-off, flight, landing and unloading states, enabling position, occupancy, queues and service times to be updated consistently.

If UAV u departs from i at time t_u^d and is expected to arrive at j after t_{uij}^{flight} , its interpolated position during the direct flight is

$$p_u(t) = p_i + \alpha_u(t)(p_j - p_i),$$

whereas p_k represent a point in cartesian position location (x_k, y_k) and

$$\alpha_u(t) = \min \left\{ 1, \max \left\{ 0, \frac{t - t_u^d}{t_{uij}^{flight}} \right\} \right\}.$$

with arrival occurring when $\alpha_u(t) = 1$ or when the remaining distance falls below a defined spatial tolerance.

The module supports fixed departures, repeated shuttles, cyclic multi-stop routes and terminal conditions, defining both where and how often each UAV operates such that,

$$(p_1, p_2, \dots, p_K, \dots, p_2, p_1),$$

With their realised frequency and utilisation are measured rather than assumed.

4.2.6 PASSENGER AND PARCEL QUEUES

Passenger and parcel queues retain requests until a compatible UAV with sufficient capacity becomes available, preserving conservation across waiting, assigned, on-board and completed states.

Requests that cannot be served immediately remain at their origin. Let $Q_i^P(t)$ and $Q_i^F(t)$ denote the passenger and parcel queues at location i . When UAV u is ready to depart, boarded passengers and loaded parcels are bounded by the available request and UAV capacity:

$$b_{ui}^P(t) = \min\{Q_i^P(t), C_u^P\},$$

$$b_{ui}^F(t) = \min\{Q_i^F(t), C_u^F\}.$$

The passenger queue update is

$$Q_{i,P}(t+1) = Q_{i,P}(t) + A_{i,P}(t) - b_{ui,P}(t),$$

and the parcel queue update is

$$Q_{i,F}(t+1) = Q_{i,F}(t) + A_{i,F}(t) - b_{ui,F}(t).$$

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

where $A_{i,P}(t)$ and $A_{i,F}(t)$ are new passenger and parcel arrivals during the simulation step. These equations preserve request conservation: a request is either waiting, assigned/on-board or completed.

Dispatch can prioritise schedule adherence, waiting time, repositioning distance, service class or a weighted combination; unserved requests remain queued.

4.2.7 FIELD-OF-VIEW-BASED DATA COLLECTION

A flying UAV may also act as a mobile traffic sensor. The field-of-view module detects ground vehicles geometrically and converts observations into traffic indicators synchronised with SUMO through TraCI.

At time t , UAV u has position

$$\mathbf{p}_u(t) = (x_u(t), y_u(t)).$$

A ground vehicle v has position

$$\mathbf{p}_v(t) = (x_v(t), y_v(t)).$$

The planar distance between the UAV projection and the vehicle is

$$d_{uv}(t) = \sqrt{(x_u(t) - x_v(t))^2 + (y_u(t) - y_v(t))^2}.$$

For a circular field of view with radius R_u^{FOV} , vehicle v is detected when

$$d_{uv}(t) \leq R_u^{FOV}.$$

For a directional sensor with heading $\theta_u(t)$ and viewing angle ϕ_u , detection additionally requires

$$|\text{wrap}(\theta_{uv}(t) - \theta_u(t))| \leq \frac{\phi_u}{2},$$

where $\theta_{uv}(t)$ is the bearing from the UAV to the vehicle and wrap maps the angle difference to a consistent interval.

For each detected vehicle, the module records, where available through TraCI: timestamp, position, speed, lane identifier, edge identifier, distance from the UAV, detecting UAV identifier, and sensor/FOV configuration.

The set of vehicles detected on edge e at time t is denoted by $V_e(t)$. The detected vehicle count and average speed are

$$N_e(t) = |V_e(t)|,$$

$$\bar{v}_e(t) = \frac{1}{|V_e(t)|} \sum_{v \in V_e(t)} v_v(t), \quad |V_e(t)| > 0.$$



A simple observed travel-time estimate for edge length ℓ_e is

$$\hat{t}_e(t) = \frac{\ell_e}{\max\{\bar{v}_e(t), \varepsilon\}},$$

where $\varepsilon > 0$ prevents division by zero. Observations can be aggregated per UAV, vehicle, lane, edge and time interval. These data support traffic-state estimation and the recalibration of network travel-time assumptions.

4.3 NEXT STEPS – INVESTIGATION OVER THE NICOSIA PILOT

The next phase of the work will focus on evaluating the proposed multimodal hub optimisation algorithm using the FEDORA Nicosia pilot. Real mobility data collected through the FEDORA Data Space will be used to generate representative origin–destination demand matrices, multimodal transport networks and infrastructure constraints for the study area. The objective is to assess the algorithm under realistic operating conditions and quantify its ability to identify efficient multimodal hub locations, infrastructure requirements and demand allocation strategies.

A comprehensive sensitivity analysis will be conducted by varying demand levels, infrastructure availability, objective-function weights and operational constraints. The resulting hub configurations and multimodal flows will be integrated with the FEDORA journey-planning and simulation components to evaluate network performance using indicators such as travel time, accessibility, infrastructure utilisation, modal distribution and operational cost.

Regarding the next phase of the UAV component, this will focus on the preparation and deployment of a real-life pilot within the Nicosia study area. Suitable UAV service locations will be identified based on operational requirements, accessibility, safety considerations and regulatory constraints. These locations will define representative hub-to-hub and hub-to-destination routes that can be evaluated under real operating conditions.

The pilot will validate the proposed UAV path-planning framework by assessing flight execution, service scheduling, repeated operations. The collected flight and sensing data will be compared with the corresponding simulation outputs to assess the realism of the operational model and support further calibration of the UAV planning framework.

PU - PUBLIC

D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

5 CONCLUSION

Deliverable D4.1, *Optimization and Incentivization Models for Multimodal Networks*, presents the mid-term results of FEDORA Work Package 4 on the development and integration of social optimum models, dynamic pricing and incentivisation mechanisms, and multimodal hub optimisation for future-oriented traffic management. The deliverable brings together the results of Tasks 4.1–4.3 and establishes the methodological and technological basis for their integration into the FEDORA simulation, data-space and pilot environments.

The work on **social optimum models** develops an algorithmic approach for signalised intersections and corridors that seeks to minimise the weighted waiting time of traffic participants. In contrast to conventional system-optimum approaches, the model assigns individual weights reflecting the desired priority of different users and modes, thereby allowing traffic management to account for fairness and policy objectives. The approach has been formulated mathematically and extended from individual intersections to interconnected corridors. For the Viennese pilot, the required multimodal data sources and data-quality requirements have been analysed, and a General Variable Neighbourhood Search (GVNS) approach has been implemented for signal optimisation. Tests on a virtual ten-intersection corridor produced a coordinated green wave and showed that good solutions can be obtained within a short computation time, supporting the planned periodic recalculation of signal plans in the pilot environment.

Dynamic pricing and incentivisation extends conventional congestion-management approaches by explicitly addressing fairness, public acceptance and the distribution of costs and benefits. The work establishes a fairness-oriented framework for evaluating traffic-management measures and investigates non-monetary mechanisms, particularly Karma-based resource allocation, as an alternative to conventional monetary pricing. In addition, the Urban Priority Pass concept demonstrates how smart-city technologies can enable individualised prioritisation at signalised intersections. Together, these approaches provide incentive layers that can complement optimisation-based traffic control and enable traffic resources to be allocated according to policy objectives, user needs or urgency rather than solely according to willingness to pay.

For **multimodal hub optimisation**, FEDORA has developed a capacity-constrained Mixed Integer Linear Programming (MILP) model that jointly determines hub locations or upgrades, available transport modes, infrastructure requirements, modal links and OD-flow allocation. The implementation is connected to FEDORA data spaces and the simulation environment and supports conventional modes as well as UAV-based services. Sensitivity analysis demonstrates the trade-offs between travel time, operating cost and infrastructure requirements. At reference demand, prioritising travel time reduced average travel time by 43.5% compared with the balanced configuration, while a cost/infrastructure-oriented configuration reduced operating cost by 48.0%, illustrating the value of explicit multi-objective planning.

The deliverable therefore provides a **coherent toolbox for optimisation and incentivisation of multimodal mobility systems**, combining operational traffic control, demand-management mechanisms and strategic multimodal infrastructure planning. The next phase will focus on validation and integration in the FEDORA pilots, including realistic mobility data, journey planning, SUMO-based simulation and UAV operations in the Nicosia pilot. This will enable the assessment of the developed approaches under realistic conditions and support their further calibration and integration into the FEDORA traffic-management applications.

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D4.1 - OPTIMIZATION AND INCENTIVIZATION MODELS FOR MULTIMODAL NETWORKS

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ANNEX - ONLINE SOFTWARE RESOURCES AND HOW-TO MANUALS

This annex provides references to the software artefacts developed within the FEDORA Data Space, including source code repositories and user documentation. The listed references include the location of the source code repositories, associated documentation (README files, user manuals, installation guides, and administrator guides), and, where applicable, the corresponding software release, version tag, or commit identifier. The referenced artefacts represent the versions available at the time of submission of this deliverable.

The tables show the current status of the software parts developed by the partners. It should be noted here that, due to data protection considerations and the sensitivity of the data used, negotiations are still ongoing regarding intellectual property rights (IPR) and whether the software components developed may be published as open-source software at all. At a later stage during the project's duration, the status regarding the release of the software components may change. In this regard, the ANNEX will be amended accordingly to provide all necessary information on the relevant software packages.

ANNEX A – SOFTWARE REPOSITORY REFERENCES

Identifier	Description	Repository	Version / Commit
fair_roads	Project source code	https://github.com/fedora-horizon/fair_roads	Release v1.0
karma_game_library	Project source code	https://github.com/fedora-horizon/karma_game_library	

ANNEX B – USER DOCUMENTATION

Document ID	Title	Location	Version
fair_roads	Docs regarding FEDORA Mobility Data Space	https://fedora-horizon.github.io/docs/harvesting/introduction/	Release v1.0
karma_literature_review	This is the online repository for the literature review paper on Karma.	https://github.com/fedora-horizon/karma_literature_review	

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urban_priority_pass	The Urban Priority Pass is a fairness-enhancing traffic light controller that leverages auctions and prioritization at signalized intersections. This is the online repository to the publication in "Transportation Research Interdisciplinary Perspectives"	https://github.com/fedora-horizon/urban_priority_pass	
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