Advanced traffic management solutions for synchronized and resilient multimodal transport services

SYNCHROMODE

D5.2: Optimisation models for transport network management

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Executive Summary

This document is the second deliverable of WP5, “Transport Network Optimisation,” which is titled D5.2, “Optimisation models for transport network management.” The manuscript gathers the results from Task 5.2, “Formulation and modelling of Transport Network Optimisation Problems.” The key aim of this task is to define the optimisation problems that will be addressed within the WP5 framework of the SYNCHROMODE project.

The content of this document builds on the findings from Task 5.1, “Review and Analyse current and future mobility approaches in Transport Network Optimization”, with a specific focus on the six optimisation problems identified in that task for WP5.

In this way, the main content of this deliverable is the formulation of six optimisation problems, namely: Synchronization of Public Transport and Demand-Responsive Transport, Freight on Transit, Advanced Cooperative Intelligent Transport Systems and Traffic Signal Control Measures, Social Routing, Roadworks Planning, and Automatic Recommendation of Interventions. Each of these problems is presented in two parts. The first part introduces the problem, followed by the mathematical formulation that will be applied in the project. The second part outlines the implementation framework, detailing its interaction of the optimiser with the transport simulator.

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Summary sheet

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List of acronyms

C-ITS	Cooperative Intelligent Transport Systems
DRT	Demand-Responsive Transport
FoT	Freight on Transit
FM	First-mile
LM	Last-mile
GLOSA	Green Light Optimal Speed Advisory
PT	Public Transport
RSU	Roadside Unit
TMC	Traffic Management Center
TSC	Traffic Signal Control
VMS	Variable Message Signs

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1 Introduction

1.1 Project Summary

The SYNCHROMODE project aims to develop a data-driven ICT toolbox for improving the management of transport operations from a multimodal perspective, to manage the transport network. SYNCHROMODE will provide transport managers with new predictive and network optimisation capabilities to balance transport supply and demand, enabling efficient reactions to different types of events. SYNCHROMODE will demonstrate through carefully selected case studies the effectiveness of integrated multimodal and multi-actor traffic and transport management solutions and the SYNCHROMODE toolbox, able to balance the demand load of both people and goods and, at the same time, reduce individual journey times.

This deliverable is linked to Task 5.2 "Optimisation models for transport network management", and presents the outcomes related to this task. The primary objectives addressed in Task 5.2 focus on formulate specific optimisation problems and developing a comprehensive modelling framework for decision variables, constraints, and objective functions relevant to transport network optimisation. In this document, we present the mathematical formulations for six key optimisation challenges: Synchronization of Public Transport (PT) and Demand-Responsive Transport (DRT), Freight on Transit (FoT), Advanced Cooperative Intelligent Transport Systems (C-ITS) and Traffic Signal Control Measures, Social Routing, Roadworks Planning, and Automatic Recommendation of Interventions.

1.2 Purpose of the document

This deliverable outlines the primary objectives from Task 5.2, "Formulation and modelling of Transport Network Optimisation problems". It focuses on formulating the optimisation problems identified in D5.1 "Analysis of current and future mobility approaches in optimisation of transport network management", and on developing the mathematical optimisation models that abstract these problems. Concretely, the six problems identified in D5.1 were: Synchronization of Public Transport and Demand-Responsive Transport, Freight on Transit, Advanced Cooperative Intelligent Transport Systems and Traffic Signal Control Measures, Social Routing, Roadworks Planning, and Automatic Recommendation of Interventions. A brief description of each of them is given below:

- The synchronisation of PT and DRT aims to enhance coverage of PT in low-service areas by optimising the deployment of DRT services that cover the first and last-mile of PT. In this project we assumed a pre-booked system where users specify departure and arrival time windows for door-to-door trips. The first goal is to identify suitable PT stops and lines that align with these time windows, followed by optimising DRT vehicle routes.

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- Freight on Transit addresses the integration of parcel delivery with PT systems, ensuring that deliveries do not disrupt passenger service quality; this involves aggregating demand and optimising vehicle capacity and route planning while synchronising deliveries with passenger trips and integrating DRT for first-mile and last-mile segments.
- Advanced C-ITS and traffic signal control measures improve traffic management through active responses to real-time conditions. They utilise Traffic Management Centers (TMCs) to enhance flow and minimise delays, with key applications including Green Light Optimal Speed Advisory (GLOSA) and PT Signal Priority.
- Social Routing aims to alleviate congestion and the environmental impact of traffic during specific events or disruptions by dynamically rerouting vehicles using different systems available for this purpose, like Variable Message Signs (VMS), Roadside Units (RSUs), and navigation apps. Concretely, it optimises the coordination of different rerouting strategies, considering the probable compliance levels of the suggested re-routed options.
- Roadworks planning optimises the schedules of the phases of a predefined set of roadworks with the aim of minimising disruption to traffic and balancing timely completion with the reduction of congestion and emissions.
- The automatic recommendation of interventions aims to recommend traffic management strategies tailored to specific road network disruptions by leveraging the previous optimisation models as well as supervised and unsupervised machine learning techniques.

1.3 Intended Audience

The dissemination level of Deliverable D5.2 is sensitive, and the document is distributed internally within the project’s consortium.

1.4 Structure of the deliverable

After outlining the key areas of interest addressed in this deliverable, the document focuses on presenting the design and formulation of optimisation problems for transport network management within WP5. Section 2 describes the optimisation model for synchronising PT and DRT. Section 3 focuses on the optimisation models and implementation approach for the optimisation of Freight on Transit systems. Then, in Section 4, we delve into Advanced C-ITS and traffic signal control measures. Subsequently, the Social Routing optimisation problems are detailed in Section 5. Following this, Section 6 presents the formulation of roadworks planning optimisation. Section 7 discusses the automatic recommendation of interventions. Finally, Section 8 gathers the main conclusions of the deliverable and outlines the links with the upcoming deliverables.

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2 Synchronization of public transport and demand-responsive transport

2.1 Formulation of the optimisation problem

The integration of public transport (PT) systems, such as buses and metros, with demand-responsive transport (DRT) has emerged as a promising solution to enhance PT coverage in areas with low-quality services, such as suburbs and rural regions. This approach seeks to optimise the deployment of a DRT fleet to complement existing PT stops and services, which is essential to addressing mobility needs in these underserved areas (Xu et al., 2022; Carlow et al., 2021).

In this problem, we are assuming a pre-booked DRT system in which the users should specify before the starting of the operations of the DRT service their preferred departure and arrival time windows for the door-to-door trip, which could include DRT + PT trip, PT + DRT trip, or DRT + PT + DRT trip. Here, it is important to mention that we do not consider door-to-doo DRT trips because, in this project, the use cases in which this module will be applied are only focused on DRT services that act as feeders and collectors of public transport. The main reason behind this is that they are meant to serve the connection of periurban and rural areas with urban areas which reduce the compatibility of first/last-mile trips with door-to-door trips. To optimise the coordination of these types of DRT services with PT, the first objective is to identify the most appropriate PT stops, as well as the PT lines and expeditions that satisfy the users' specified time windows. This process is critical, as the correct identification of PT stops and lines can maximise the efficiency of the integrated transportation system, thereby facilitating access for users in rural and suburban areas (Zhou et al., 2019).

Once the optimal stops and expeditions are identified, the DRT service requests to cover the first-mile and the last-mile are established according to the specified departure and arrival time windows and the schedules of the selected PT lines. Subsequently, the focus shifts to optimising the DRT vehicle routes that will serve the established DRT service request. This is known as the Dial-a-Ride Problem (DARP), a well-established combinatorial optimisation problem in the scientific literature. The DARP involves assigning vehicles to pick up passengers from an origin and drop them off at a destination while adhering to various constraints, such as time windows (Dong et al., 2020). The challenge is to determine the optimal routes that ensure all clients are served within their specified time limits.

The variant is known as the Dial-a-Ride Problem with Time Windows (DARPTW) (Belhaiza et al., 2022; Maliki et al., 2023). As Schenekemberg et al. (2022) and Ham (2023) explain, the DARP simulates a DRT mode with the goal of generating a set of routes that fulfil passenger requests at the lowest possible cost. Each request involves transporting a passenger from their origin to their destination, with the possibility of sharing a vehicle with other passengers if they are travelling on similar routes and within the same time frames, provided there is available space.

In order to carry out this integration, the general operation of the optimisation framework, schematically represented in Figure 1.

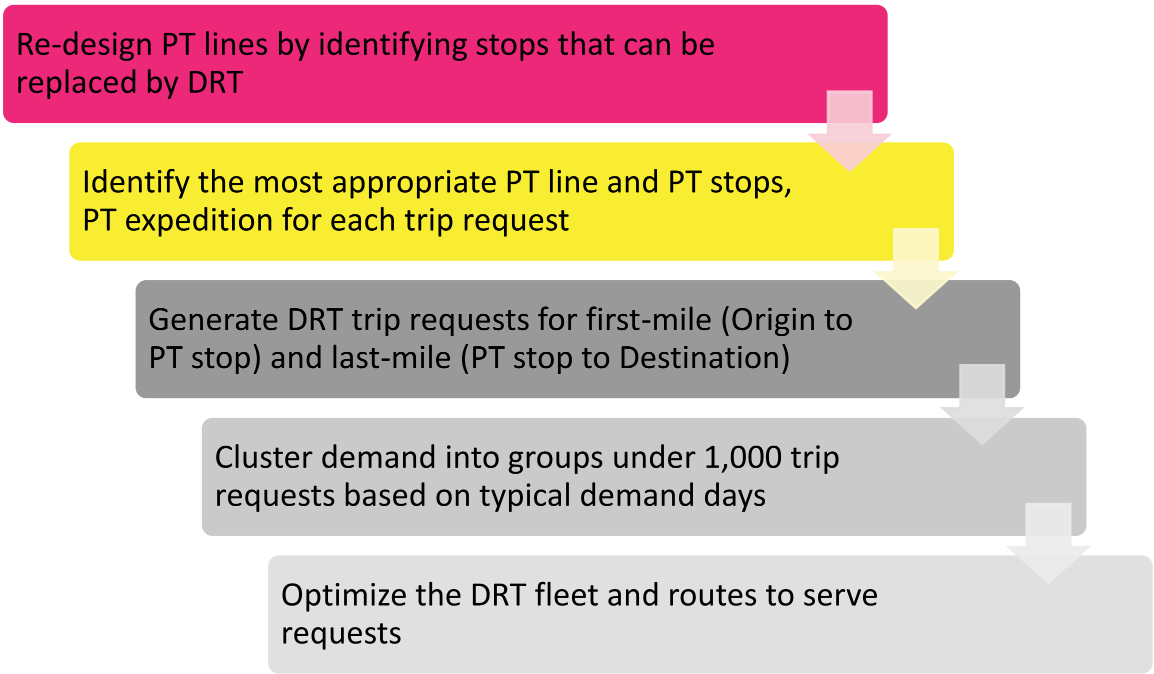

Figure 1: General operation for the synchronization of PT and DRT optimisation problem

2.1.1 Public transport lines re-design for demand-responsive transport

To achieve effective synchronization between PT and DRT, it is essential to identify which of the existing PT routes and stops would be better suited for replacement by DRT services. The key considerations for identifying PT stops that may be replaced and synchronized with DRT are:

- The stops to be replaced shall correspond with stop sequences at the end or beginning of the routes, so that they can be effectively synchronised with the rest of the PT routes both for passenger and parcel transportation.
- The stops considered for replacement by DRT should meet at least one of the following criteria:
    - The PT services at these stops are either not frequent enough or not sufficiently accessible within their transport zone, and there is a considerable demand for a more personalized service. To assess this, a PT needs index and a PT availability index are

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calculated per zone. Zones with a high PT needs index and a low PT availability index are prone to DRT synchronisation.
    - The demand for PT at these stops is very low, making DRT a more efficient option to meet this demand. This can be determined by analysing the number of trips with origin or destination at these stops, or general PT usage within these areas.

Based on the defined set of KPIs, a ranking with proposed stop sequences to be replaced and synchronised with DRT is generated.

2.1.2 Public transport stop, public transport line and public transport expedition assignment

The process of PT assignment aims at identifying the most suitable PT stops, lines, and specific expeditions for each trip request, ensuring that users experience minimal waiting times and reduced travel distances. This task is achieved by employing the Public Transport Assignment Optimisation Function (*PTAOF*), which selects stops, lines, and expedition times based on the user's origin, destination, and time window preferences.

The goal is to assign each trip to PT stops (for both origin and destination), along with the appropriate transport line and specific expedition (departure time), to match the user's desired departure or arrival time, thereby minimizing total journey time. This includes reducing both the waiting time for PT services and the travel distance. The *PTAOF* evaluates nearby PT stops, available lines, and expeditions, selecting the optimal combination to meet the user's scheduling needs.

The key concepts for the PT stop, line, and expedition assignment process are:

- Scheduling Constraints: Users specify a desired departure time or a range of acceptable arrival times. The selected PT stops, lines, and expeditions must align with these time windows. The *PTAOF* evaluates which stops, lines, and expeditions can serve the user within these constraints, aiming to minimize both waiting time and total travel distance.
- Optimisation: The *PTAOF* optimizes the selection of PT stops, lines, and expeditions by balancing proximity to the user, availability of PT lines, and the user's scheduling preferences. The solution selects stops, lines, and expeditions that minimize both waiting time and travel distance.

The objective function *PTSOF* facilitates the effective scheduling of the DRT service and can be expressed as follows:

$$min \quad PTSOF = \sum_{u \in U} \sum_{z \in Z} \sum_{\substack{(m,n) \in N_z^2 \\ m \neq n}} [\alpha_1 x_{uzmn} d_{zmn} + \alpha_2 w_u] \qquad (1)$$

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$$\begin{array}{lllr} s.t. & a_u \leq t_{dep_u} \leq b_u, & \forall u \in U & (2) \\ & t_{arr_u} \leq b_u, & \forall u \in U & (3) \\ & t_{arr_u} \leq t_{dep_u} + t_{walking_{uzm}}, & \forall u \in U & (4) \\ & \sum_{u \in U} y_{uzi} q_u \leq Q_z^{PT}, & \forall z \in Z, \forall i \in N_Z & (5) \end{array}$$

The notation used for the formulation (1) of the *PTSOF* is as follows:

- x_{uzmn} indicates whether user *u* travels from node *m to node n* on transport line z.
- t_{zmn} is the travel time between origin stop m and destination stop n on transport line z.
- w_u is the waiting time of user *u* at the origin stop, defined as $w_u = t_{dep_u} - a_u$.
- y_{uzi} represents the number of users using stop i on line z, defined as $y_{uzi} = \sum_{(m,n)\in N_Z^2} x_{uzmn} \cdot 1[m \leq i < n]$.
- α_1, α_2 are the coefficients that weight the importance of each of the components in the objective function.

The formulation of the *PTSOF* is subject to several constraints. The constraint (2) ensures that the departure time for user *u* (t_{dep_u}) falls within their specified time window $[a_u, b_u]$, guaranteeing that users depart at their preferred times. Additionally, constraint (3) ensures that the arrival time t_{arr_u} at the destination stop does not exceed the latest allowable arrival time b_u specified by the user. Furthermore, constraint (4) imposes that the arrival time must be greater than or equal to the sum of t_{dep_u} and $t_{walking_{uzm}}$ (the walking time from the user's location to the selected PT stop *m* on line *z*). Finally, constraint (5) ensures that the total demand of users assigned to each stop i on transport line *z* does not exceed the PT's capacity Q_z^{PT}, ensuring the feasibility of operations without overloading. Giving that q_u represents the number of passengers that are requesting for the service.

2.1.3 First-Mile/Last-Mile trip request generation

The process of First-Mile/Last-Mile (FM/LM) trip request generation involves creating specific travel requests that meet user needs during their transitions: from their origin to the assigned PT stop in the FM segment, and from the subsequent PT stop to the user's final destination in the LM segment.

To address these FM and LM legs, the optimisation framework generates two DRT service requests: one for the first-mile and another for the last-mile. If the trip requested by the user can be served in a better way using only public transport, with no need for DRT to cover the first of the last-mile, the system will detect it and will not generate this trip request for DRT.

Each DRT service request consists of four key elements: origin, time-window for departure, destination and time-window for arrival. The time windows at PT stops are defined based on the schedule of the selected PT trip and a maximum waiting time, defined by δ_{wait}, that aims at limiting the waiting time of the user at the PT stop before he/she takes the public transport in the first mile, or he/she is pick-up by the DRT vehicle in the last-mile.

The DRT request generation process can be detailed as follows:

- FM request: $FM_j = \{O_j, [T_s^{O_j}, T_e^{O_j}], PT_{stop}^{k_1}, [t_{dep}^{k_1} - \mu, t_{dep}^{k_1} - \delta_{wait}]\}$, where O_j is the origin of user j, and $[T_s^{O_j}, T_e^{O_j}]$ represents the time window for departure from origin. $PT_{stop}^{k_1}$ is the selected PT stop for FM segment, and $[t_{dep}^{k_1} - \mu, t_{dep}^{k_1} - \delta_{wait}]$ represents the time window at the PT stop, defined by the departure time $t_{dep}^{k_1}$ of the PT service, accounting for the buffer time μ and the maximum waiting time δ_{wait}.
- LM request: $LM_j = \{PT_{stop}^{k_2}, [t_{arr}^{k_2} + \mu, t_{arr}^{k_2} + \delta_{wait}], D_j, [T_s^{D_j}, T_e^{D_j}]\}$, where $PT_{stop}^{k_2}$ is the selected PT stop for the LM segment, and $[t_{arr}^{k_2} + \mu, t_{arr}^{k_2} + \delta_{wait}]$ represents the time window at this PT stop, based on the arrival time $t_{arr}^{k_2}$ of the PT service, with the buffer time μ and the maximum waiting time δ_{wait} considered. D_j is the final destination of user j, and $[T_s^{D_j}, T_e^{D_j}]$ defines the time window for arrival at the destination.

This systematic approach integrates both FM and LM requests into a unified travel plan for users. By ensuring that each segment adheres to the time windows specified by the user and connects efficiently with the PT service, the DRT framework significantly enhances the overall efficiency of the transportation system.

Finally, this method facilitates a smooth transition between DRT and PT, addressing individual user needs and leading to improved user satisfaction and increased utilization of integrated transport services. The final DRT request for the user can be summarized as:

$$\text{DRT Request} = (FM_j, LM_j)$$

2.1.4 Demand clustering

The demand clustering process aims at making the optimisation process more scalable and efficient by establishing a divided and conquer strategy. Its main objective is to group user travel requests into clusters to optimise transportation resources and improve service efficiency.

The key objectives of the clustering process are:

- Identify typical demand days, ensuring that the clustering accounts for variations in demand based on time (e.g., weekdays, weekends, or holidays).
- Grouping the trip requests into manageable clusters, each containing fewer than 1,000 requests to ensures that the optimisation algorithms can process each group and assign appropriate PT stops.

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This clustering process results in groups of trip requests with nearby origins and destinations, paired with potential PT stops. The clustering can be formally defined as a function C, where $C: R \rightarrow G$. In this context, R represents the set of DRT requests generated in the previous step, and G denotes the set of clusters formed. The output of the function C is a mapping that assigns each DRT request $r \in R$ to its corresponding cluster $g \in G$. Specifically, for any given DRT request r, the function $C(r)$ identifies the cluster g to which r belongs, thus facilitating subsequent optimisation steps by ensuring that similar trip requests are grouped together.

By clustering trip requests, the system reduces the number of potential stop combinations, making the optimisation task more manageable. This also ensures that similar travel demands are addressed together, enhancing the efficiency and effectiveness of the DRT service.

2.1.5 Demand-responsive transport service optimisation

This process involves optimising both the fleet of vehicles and the routes taken to address DRT requests generated during the FM and LM segments of the journey.

In contrast to the basic DARPTW, which solely aims to minimise the distance travelled, this model seeks to minimise several key factors, including total distance travelled, travel times, energy consumed by vehicles, and operational costs. To achieve these objectives, the model is formulated as a Multi-Criteria Total Transport Cost Function (*MCTTCF*)**.** This function simultaneously considers multiple objectives to optimise the overall transportation process. The *MCTTCF* can be mathematically expressed as follows:

$$min \quad MCTTCF = \sum_{u \in U} \sum_{k \in K} \sum_{\substack{(i,j) \in N^2 \\ i \neq j}} x_{uijk} \left[\alpha_3 d_{ij} + \alpha_4 t_{ij} + \alpha_5 e_{ij} + \alpha_6 c_{ij} \right] \qquad (6)$$

$$\begin{aligned}
s.t. \quad & a_u \leq t_{pickup_u} \leq b_u, && \forall u \in U && (7) \\
& t_{delivery_u} + t_{ij} \leq b_u, && \forall u \in U && (8) \\
& \sum_{u \in U} \sum_{(i,j) \in N^2} q_u x_{uijk} \leq Q_k^V, && \forall k \in K && (9) \\
& \sum_{k \in K} \sum_{j \in N} x_{u,depot,j,k} = 1, && \forall u \in U && (10) \\
& \sum_{k \in K} \sum_{i \in N} x_{u,i,depot,k} = 1, && \forall \mathrm{u} \in \mathrm{U} && (11) \\
& \sum_{k \in K} \sum_{(i,j) \in N^2} x_{uijk} = 1, && \forall u \in U && (12)
\end{aligned}$$

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The notation used for the formulation (6) of the *MCTTCF* is:

- x_{uijk} indicates whether vehicle k travels from node i *to node* j for user u.
- d_{ij} is the distance between nodes i and j.
- t_{ij} is the travel time between nodes i and j.
- e_{ij} represents the energy consumed between nodes i and j.
- c_{ij} is the operational cost between nodes i and j.
- $\alpha_3, \alpha_4, \alpha_5, \alpha_6$ are the coefficients that weigh the importance of each component in the objective function. These weights are set by the program operator, specifically the individual managing the transportation logistics. This arrangement allows for flexibility in adjusting the objective based on the specific priorities and goals of the logistics operations.

In order to formulate the DRT service optimisation, several constraints must be considered to ensure the feasibility of the system. First, for each user u in the set of customers U, the pickup time t_{pickup_u} must fall within the specified time window, meaning that it should be greater than or equal to a_u and less than or equal to b_u, as stated in constraint (7). Additionally, the delivery time for user u ($t_{delivery_u}$) plus the travel time t_{ij} to the PT stop must not exceed the maximum allowable time b_u for each customer u in constraint (8).

Moreover, there are capacity constraints in place to ensure that the total demand q_u of users assigned to each vehicle k does not exceed its capacity Q_k^V, as outlined in constraint (9). Furthermore, to ensure operational consistency, constraints (10) and (11) impose that each vehicle k departs from the depot exactly once, indicated by the decision variable $x_{u,depot,j,k}$, and returns to the depot once after completing its route, as represented by $x_{u,i,depot,k}$. This guarantees that every vehicle has a well-defined start and end point in the route, ensuring efficient and synchronised integration between PT and DRT services. Finally, constraint (12) ensures that every request is served by exactly one vehicle. It guarantees that for each user u at node i to a destination node j, as described by the decision variable x_{uijk}. This ensures that no request is left unserved.

2.2 Implementation approach

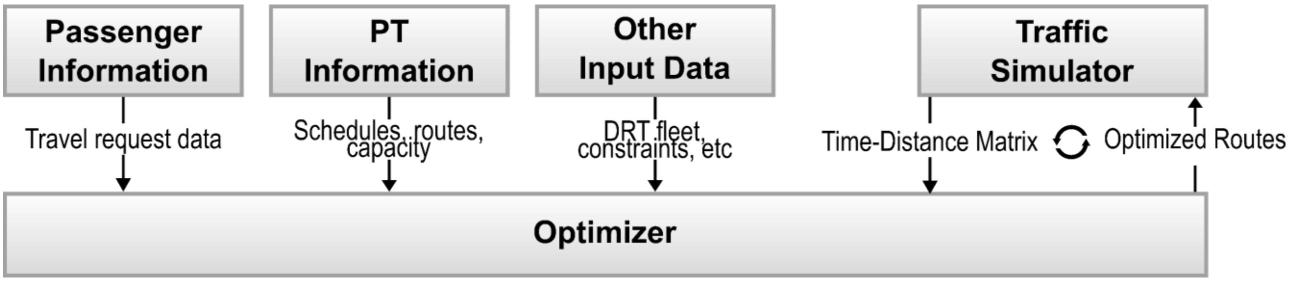

Figure 2: Schematic diagram for the synchronization between PT and DRT optimisation problem

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The implementation approach integrates the proposed optimisation model with the Transport Simulator, which is used to simulate more realistic traffic conditions, specifically focusing on the synchronisation between DRT and PT systems. The aim is to optimise both FM and LM logistics by using real-time data to enhance vehicle routing and scheduling while minimising operational costs and improving service efficiency. Figure 2 presents the diagram for this optimisation problem.

The design of the optimisation model revolves around processing various data inputs, each coming from distinct sources, and feeding them into the optimisation algorithm. These inputs are grouped into the following blocks:

- Demand Information: This block represents the DRT demand that needs to be served. This demand will be generated in WP3 and includes information such as origin and destination points, time window requirements, and priority-based scheduling. This data is essential for determining optimal vehicle allocations and routing, ensuring that passenger transport demands are met efficiently.
- PT Information: PT schedules, routes, and capacity details are included in this block. It contains static data on PT services, including the availability of routes and stop locations. This information is required to synchronise DRT services with PT, facilitating seamless transfers between transport modes and improving service coordination.
- Other Input Data: This block focuses on DRT fleet characteristics, such as vehicle types, energy consumption, operational costs, and other constraints related to the DRT fleet.
- Traffic Simulator: The simulator generates a time-distance matrix that feeds the VRP optimiser, which is essential for accurate estimations of travel times and distances between locations. It will also be used to simulate the DRT routes delivered by the VRP optimiser in real traffic conditions.

All these data blocks feed into the Optimizer, which computes optimal routing and scheduling strategies. As mentioned above, the optimisation model minimises overall operational costs (energy consumption, travel distance, and waiting times) while meeting demand and ensuring synchronisation between DRT and PT systems, resulting in an efficient and integrated multimodal passenger transport network.

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3 Freight on Transit

3.1 Formulation of the optimisation problem

The integration of PT systems with parcel delivery services, known as Freight on Transit (FoT), represents a promising solution to address the growing demand for urban freight transport by leveraging existing PT infrastructure. This dual-purpose approach enables the simultaneous transport of passengers and parcels in the same PT vehicles, maximising resource utilisation and improving the efficiency of PT systems (Masson et al., 2017; Xie et al., 2020). In addition, some of the final PT stops will be equipped with parcel lockers, allowing customers to conveniently pick up their shipments (Zhang & Cheah, 2024).

The challenge lies in ensuring that parcel deliveries do not interfere with passenger service quality. To achieve this, the system aggregates parcel demand alongside passenger demand and clusters these demands to optimize vehicle capacity and route planning. The objective is to allocate parcels to PT services with available capacity, ensuring that passenger comfort and service reliability remain unaffected (Alho et al., 2021; Shen et al., 2016). By estimating the available occupancy of PT vehicles, services with low passenger loads can be identified as eligible for parcel allocation (Zhang et al., 2023).

Once the PT vehicles and stops with sufficient capacity are identified, the system focuses on synchronising parcel deliveries with passenger trips. This includes determining optimal PT stops for both the pick-up and delivery of parcels while also considering the needs of passengers. Then, the DRT service is designed to handle first-mile (from the parcel's and passenger's location to a PT stop) and last-mile (from the PT stop to the final destination) transport segments, effectively complementing the PT service.

The resulting problem, which resembles the DARPTW, requires vehicles to transport both passengers and parcels while respecting various constraints such as vehicle capacity and time windows. The complexity arises from balancing the load between passengers and parcels to ensure that both are transported efficiently without compromising service quality.

Optimising the routes for both passenger and parcel transport can reduce operational costs while maintaining high service standards. Additionally, by leveraging existing PT infrastructure, FoT contributes to the reduction of traffic congestion caused by separate delivery vehicles, thus promoting more sustainable urban logistics (Chen et al., 2019). This framework ensures efficient, environmentally friendly urban PT, enhancing both passenger services and freight transport.

The general operation of this optimisation framework, which integrates passengers and parcels, is schematically represented in Figure 3.

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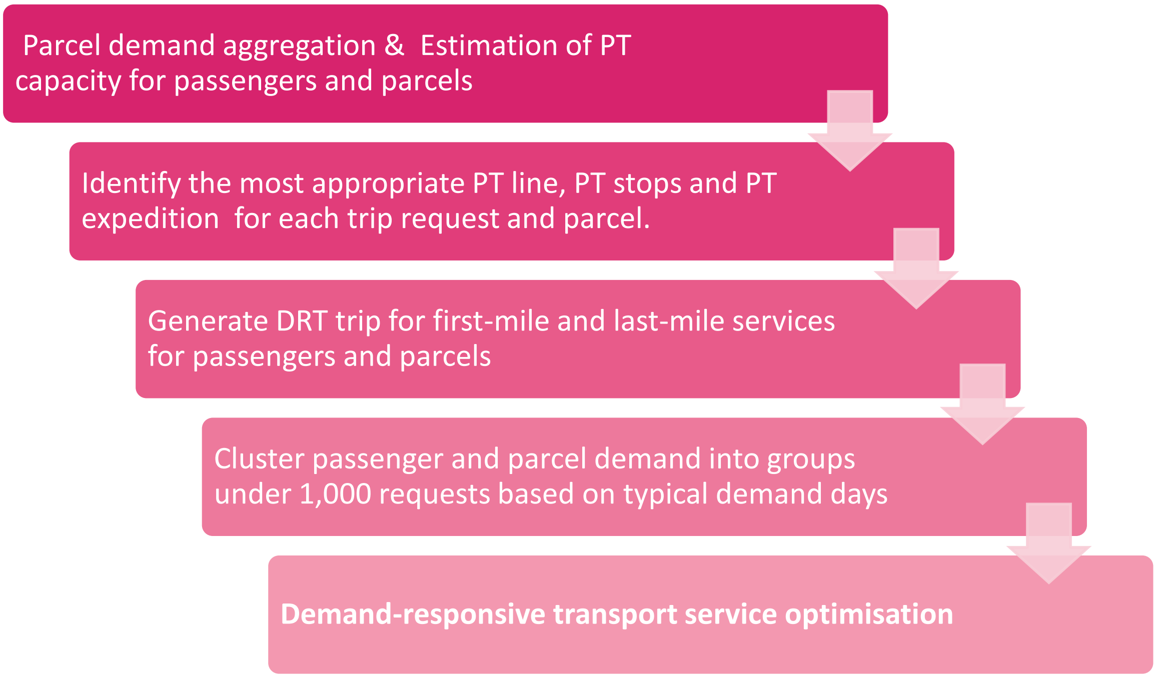

Figure 3: General operation for the freight on transit optimisation problem

3.1.1 Parcel demand aggregation

Effective aggregation of parcel demand is crucial for successfully integrating the FoT into existing PT systems and synchronizing with DRT. This process involves consolidating parcels to ensure minimal disruption to passenger services while preparing for subsequent deliveries to microhubs or parcel lockers after the first-mile segment (Cavagnini & Morandi, 2021).

To achieve this, a thorough analysis of parcel demand aggregation focuses on the following key considerations:

- Identification of Parcel Demand: The focus is on recognizing and consolidating parcel demands within the transportation network, ensuring that these demands can be grouped effectively for later distribution.
- Dynamic Capacity Assessment: The ability to aggregate parcel demands may vary throughout the day and week. Understanding the temporal dynamics of passengers is essential to determine when and where parcels can be effectively consolidated without impacting passenger services.
- Proximity for Final Deliveries: After aggregation, attention should be paid to the proximity of microhubs or parcel lockers for the last-mile delivery. This ensures efficient routing and timely delivery to the final destination, enhancing the overall effectiveness of the transport network (Yuen et al., 2018).

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3.1.2 Estimation of public transport capacity for passengers and parcels

To successfully integrate the transportation of passengers and parcels in the same PT vehicles, parcels should not interfere with passenger transportation or reduce the quality of the service currently being offered. To this end, we will only allocate parcels to those services that are expected to have a low occupancy, for which we estimate that there will be available extra space. For this purpose, we need to know beforehand what PT expeditions will have sufficient capacity for parcel allocation after considering passenger demand. Knowing a vehicle's characteristics, such as its total available space when empty, or the maximum number of passengers that it can accommodate, an estimation of future passenger demand is equivalent to an estimation of future available capacity. Taking this into account, we will estimate the passenger demand or occupancy for each PT vehicle, so that we can work out the services that are eligible for parcel allocation.

In particular, a model predicting the PT passenger demand will be trained for each interstation or consecutive pair of stops in a PT bus line. The features to be explored as predictors will be calendar variables, holidays' information, lagged features (e.g., the PT demand for the same time and day of the previous week), average PT demand for similar past days, or weather variables (e.g., rainfall or temperature), among others.

Since the PT supply might be different from day to day, the PT demand for the next day will be estimated in time intervals of, for example, 15 minutes. This information will then be compared with the supply information (planned times at which the buses will reach each station) and the estimated demand will be allocated to one or another vehicle based on their time of arrival. With this, an estimation of PT demand for each individual vehicle at any point of its route is obtained, and with it the available capacity for parcels can be computed.

3.1.3 Public transport stop, public transport line and public transport expedition assignment

The process of PT assignment aims at identifying the most suitable suitable PT stops, lines, and specific expeditions for both passengers and parcel deliveries, ensuring that users experience minimal waiting times and reduced travel distances. This is achieved through an addition of a new constraint of the *PTSOF* in formulation (1) of Section 2.1.2., which now considers both types of demand and their respective impacts on PT capacity.

$$min \quad PTSOF = \sum_{u \in U} \sum_{z \in Z} \sum_{\substack{(m,n) \in N_z^2 \\ m \neq n}} [\alpha_1 x_{uzmn} d_{zmn} + \alpha_2 w_u] \qquad (1)$$

The *PTSOF* evaluates nearby PT stops, available lines, and expeditions, selecting the optimal combination to fulfill the scheduling needs of both passengers and parcels. This involves integrating an additional constraint into the *PTSOF* in formulation (1) of Section 2.1.2. This constraint ensures

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that the assignment process accommodates the respective impacts of passenger and parcel demand on PT capacity.

The constraints for this mathematical formulation, along with the notation used throughout, are detailed in Section 2.1.2. The new constraint (13) has been introduced to ensure that the total demand from parcels assigned to each stop i on transport line z from parcels assigned to each stop does not exceed the transport line's parcel capacity Q_z^p:

$$\sum_{u \in U} y_{pzi} q_u \leq Q_z^p, \qquad \forall z \in Z, \forall i \in N_Z \qquad (13)$$

where y_{pzi} represents the number of parcels using stop i on line z, defined as $y_{pzi} = \sum_{(m,n) \in N_Z^2} x_{pzmn} \cdot 1_{[m \leq i < n]}$.

The goal is to assign each trip—whether passengers or parcels— to the most suitable PT stops while minimising travelled distance and waiting periods for the users.

To further enhance convenience for customers, parcel lockers will be installed at designated PT stops. This setup allows users to collect parcels at their convenience, reducing the need for separate delivery trips and contributing to a more efficient urban logistics system while ensuring passenger service reliability.

3.1.4 First-Mile/Last-Mile trip request generation

The process for FM/LM trip request generation focuses on creating travel requests that accommodate both passenger and parcel needs, ensuring smooth transitions from the user's origin to the nearest optimal PT stop and from the subsequent PT stop to the final destination.

This request generation process retains the principles outlined in Section 2.1.3 while enhancing its framework to address parcel deliveries alongside passenger trips. In this context, the optimisation framework generates two DRT service requests one for the first-mile ($FM_{j,p}$) for each passenger j or parcel p, and another for the last-mile ($LM_{j,p}$).

This systematic approach effectively integrates both FM and LM requests into a unified travel plan for users, ensuring that each segment adheres to the specified time windows while efficiently connecting with the PT service. By including parcel requests alongside passenger requests, the DRT framework enhances the overall efficiency of the transportation system.

Furthermore, parcel lockers will be strategically located at PT stops to facilitate the customer pickup of parcels. This integration allows users to manage their deliveries at any time and minimizes the time required by DRT drivers to distribute parcels.

The final DRT request encompassing both passengers and parcels can be summarised as:

$$\text{DRT Request} = (FM_j, LM_j, FM_p, LM_p)$$

3.1.5 Demand clustering

As detailed in section 2.1.4, the demand clustering process is crucial for optimising the integration between PT and DRT systems by grouping travel requests into clusters. Building on this methodology, the same principles apply to the case of FoT, where both passenger travel requests and parcel deliveries are clustered to optimize resource utilisation and improve overall system efficiency.

The primary objective of the clustering process in FoT is to ensure that both trip and parcel demands are grouped based on their proximity to PT stops, allowing for optimal resource allocation. However, additional considerations are introduced in FoT, such as the weight and volume of parcels in each cluster, as well as the capacity limitations of PT vehicles.

This clustering process results in groups of travel requests and parcel deliveries with nearby origins and destinations, paired with potential PT stops. The clustering can be formally defined as a function C, where $C: P \rightarrow G$. Here, P represents the set of trip requests and parcel deliveries generated in the previous step, and G denotes the set of clusters formed. The output of the function C is a mapping that assigns each trip request or parcel $p \in P$ to its corresponding cluster $g \in G$. Specifically, for any given request or parcel p, the function $C(p)$ identifies the cluster g to which p belongs, thus facilitating subsequent optimisation steps by ensuring that similar demands are grouped together.

By clustering both trip requests and parcel deliveries, the system reduces the number of possible combinations of stops and routes, making the optimisation task more manageable. This also ensures that similar demands are addressed together, enhancing the efficiency and effectiveness of the FoT service.

3.1.6 Demand-responsive transport service optimisation

Analogous to the process previously outlined in Section 2.1.5, this phase focuses on optimising vehicle fleets and routes to efficiently address DRT requests generated during the FM and LM segments.

In this context, the mathematical formulation is still defined as follows:

$$min \quad MCTTCF = \sum_{u \in U} \sum_{k \in K} \sum_{\substack{(i,j) \in N^2 \\ i \neq j}} x_{uijk} \left[\alpha_3 d_{ij} + \alpha_4 t_{ij} + \alpha_5 e_{ij} + \alpha_6 c_{ij} \right] \tag{6}$$

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Since passenger and parcel capacities are independent, the MCTTCF does not require significant modifications; each type of capacity will have its own constraints without affecting the optimisation of the other. The formulation must account for two separate capacities:

- Passenger Capacity: The maximum number of passengers a vehicle k can accommodate $Q_k^{V_u}$.
- Parcel Capacity: The maximum number of parcels a vehicle k can accommodate $Q_k^{V_p}$.

3.2 Implementation approach

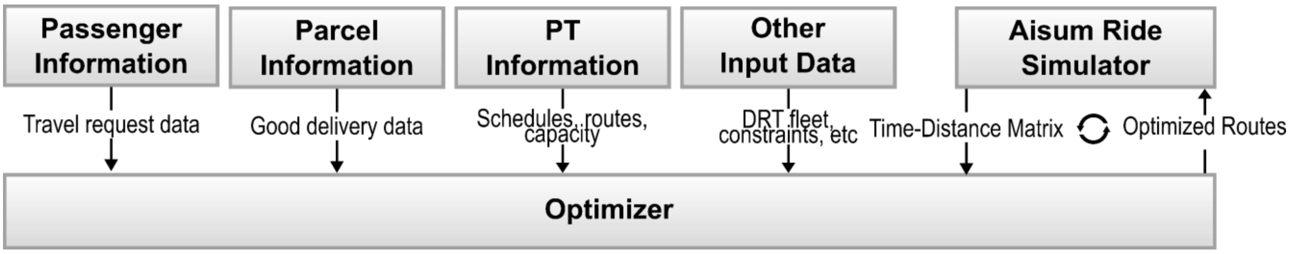

Figure 4: Schematic diagram for the freight on transit optimisation problem

The implementation approach for FoT is similar to the model outlined in Section 2.2, with the addition of a new block dedicated to parcel delivery management. This enhanced model simultaneously addresses both passenger and parcel transport, leveraging existing PT infrastructure to optimize multimodal logistics. Figure 4 presents the updated diagram for this optimisation problem, now reflecting the integration of parcels alongside passenger trips.

The optimisation model processes various data inputs, which are grouped into the following blocks:

- Passenger Demand Information: This block is analogous to the one described in previous section.
- Parcel Demand Information: This block specifically manages parcel delivery data. It includes details such as parcel size, origin, destination, and time window constraints for pickup and delivery. By factoring in this data, the model ensures that parcels are transported within the available PT capacity without disrupting passenger services. The block also considers specific parcel lockers installed at PT stops, enabling efficient handovers and reducing the need for separate delivery trips.
- PT Information: This block is analogous to the one in the previous section, but it is enhanced to track the capacity of PT vehicles for parcel transport at each stop, considering both passenger and parcel loads. It ensures that parcel assignments align with available PT capacity and passenger comfort.
- Other Input Data: This block provides details about the DRT fleet, vehicle types, energy consumption, operational costs, and any constraints related to both passenger and parcel transport. The DRT fleet serves as the connection for first-mile (FM) and last-mile (LM) segments, ensuring efficient movement of both passengers and parcels to and from PT stops.

- Aimsun Ride Simulator: This block is analogous to the one in the previous section.

The optimiser combines data from these blocks, incorporating the additional constraint that ensures parcel assignments do not exceed PT vehicle capacity at any given stop. The objective remains to minimise operational costs (e.g., energy consumption, travel distance, and wait times) while ensuring synchronisation between DRT and PT systems for passengers and parcels.

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4 Advanced Cooperative Intelligent Transport Systems and Traffic Signal Control Measures

4.1 Formulation of the optimisation problem

In recent years, Traffic Management Centers (TMCs) have evolved from passive operators into active managers of transport networks, driven by the integration of Cooperative Intelligent Transport Systems (C-ITS) and advanced algorithms for real-time traffic signal control. This transformation emphasises the need for dynamic, adaptive responses to evolving traffic conditions. By incorporating C-ITS services and advanced algorithms for real-time traffic signal control, TMCs are better equipped to optimise traffic flow both along the network as well as at signalised intersections. These systems are able to work in harmony and thus to minimise delays, promote safety, and improve overall efficiency. Moreover, the real-time data provided by connected vehicles enhances the TMCs' ability to anticipate and manage traffic conditions, ensuring seamless integration across various systems. As a result, the following C-TS applications and traffic signal control methods at signalised intersections will be formulated and described below:

1. Green Light Optimal Speed Advisory (GLOSA) – Eco-driving
2. Public Transport Signal Priority (PuT Signal Priority)
3. Max-pressure Traffic Signal Control (Max-pressure TSC)

4.1.1 Green light optimal speed advisory – eco-driving

Green Light Optimal Speed Advisory (GLOSA) is a Cooperative Intelligent Transport System (C-ITS) application that aims to promote eco-driving by advising drivers on the optimal speed to pass through signalised intersections during the green phase, thus minimising stops at red lights. GLOSA is designed to reduce fuel consumption, greenhouse gas emissions, and travel delays by helping drivers maintain a smooth driving pattern, avoiding the stop-and-go behaviour that often characterises urban driving.

GLOSA operates by integrating real-time traffic signal data with vehicle-specific parameters such as location, speed, and route. When a vehicle equipped with GLOSA approaches a signalized intersection, the system communicates with the traffic signal controller to retrieve information about the current and upcoming traffic signal phases. Based on this data, the system calculates the optimal speed for the vehicle to pass through the intersection during the green phase. This speed recommendation is then communicated to the driver via an in-vehicle display, connected smartphone application, or other driver-assistance systems.

The calculation of optimal speed considers multiple factors:

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- Current vehicle speed: The system identifies how fast the vehicle is travelling and adjusts the speed recommendation accordingly.
- Signal phase timing: GLOSA accounts for the time remaining in the current signal phase, whether it is green, yellow, or red.
- Distance to intersection: The distance between the vehicle and the intersection is crucial in determining how much the vehicle needs to slow down or accelerate to reach the intersection during the green light.

GLOSA service is highly effective, especially in urban environments, where frequent stops at red lights lead to higher fuel consumption and emissions. By advising drivers to maintain an optimal speed, GLOSA reduces the need for stop-and-go driving, which is one of the leading causes of inefficiencies in urban traffic networks.

One of the key benefits of GLOSA is its ability to support eco-driving, a driving behaviour focused on minimizing fuel consumption and emissions. By helping drivers avoid unnecessary stops at red lights, GLOSA reduces fuel wasted during acceleration and idling. This reduction in stop-and-go traffic leads to lower carbon dioxide (CO_2) emissions, benefiting both the environment and the vehicle’s operational efficiency. Moreover, the smoother traffic flow facilitated by GLOSA improves overall traffic throughput, reducing delays for all road users.

Despite its advantages, implementing GLOSA in real-world traffic systems presents several challenges. Traffic conditions are inherently dynamic and unpredictable, with traffic patterns varying significantly depending on factors like time of day, congestion, and real-time adjustments made by Traffic Management Centers (TMCs) to signal timings. GLOSA service must be capable of continuously adapting to these conditions, requiring robust decision-making mechanisms that can efficiently handle fluctuating inputs. Additionally, GLOSA service must balance multiple, often conflicting objectives. The system also needs to ensure that general traffic flow remains smooth and efficient for all road users, including pedestrians. This creates a complex optimisation problem, as GLOSA service must reconcile the demands of different transportation modes, preventing bottlenecks while still achieving energy savings and emissions reductions. (Alegre et al., 2021)

Given the complexity of modern urban traffic systems, reinforcement learning (RL) presents an optimal solution for improving the performance of GLOSA by dynamically adapting to changing traffic conditions. RL-based GLOSA can learn from real-time traffic data and continuously update its recommendations based on the current traffic environment, vehicle behaviour, and traffic signal timings. This enables GLOSA to provide speed advisories that are not only responsive but also optimized for reducing emissions and fuel consumption.

In an RL framework, GLOSA agents (vehicles) interact with their environment (traffic system), receiving rewards based on how well they optimize traffic flow and minimize emissions. These agents continuously refine their decision-making process through trial and error, learning how to

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balance the competing objectives of eco-driving, public transport priority, and general traffic management.

To handle the decentralised nature of urban traffic systems, a Multi-Agent Reinforcement Learning (MARL) approach is particularly effective for GLOSA. Each vehicle operates as an independent agent that learns its own optimal strategy for responding to the current state of traffic signals. By using MARL, GLOSA can handle varying traffic conditions across multiple intersections without needing pre-defined domain knowledge or specific network topology information.

In MARL, agents learn optimal policies by associating their current state (e.g., speed, distance to intersection) with the best action (e.g., accelerating, maintaining speed) to maximise cumulative rewards (e.g., minimising emissions, reducing delays). This decentralized learning approach allows each agent to make decisions independently while still contributing to the overall traffic management goals of the system.

The state space in the GLOSA system represents the current traffic conditions at a signalised intersection and the status of the approaching vehicle. Each state $s_t$at time t is defined by a vector of observable variables that describe the traffic environment. This includes:

- Signal phase: The current traffic light phase (green, yellow, red) for the relevant direction.
- Elapsed time in phase: The time elapsed in the current traffic signal phase, which affects when the phase will change.
- Vehicle information: This includes the approaching vehicle's current speed, position relative to the intersection, and acceleration or deceleration rates.
- Traffic density and flow: The number of vehicles approaching the intersection from different directions, as well as any public transport priority vehicles.

In the GLOSA context, the state space provides the essential information required to calculate the optimal speed for the approaching vehicle to either pass through the green light or reduce delay when stopping.

The action set defines the possible actions that the system can take at each time step. For GLOSA service, the primary action is to recommend an optimal speed to the driver (longitudinal acceleration of the vehicle). The action space consists of:

- Maintain current speed: If the current speed will allow the vehicle to pass through the green light or minimise waiting time.
- Increase speed: If accelerating slightly, it will enable the vehicle to pass through the intersection during the green phase.
- Decrease speed: If decelerating will result in a more efficient stop or allow the vehicle to arrive at the intersection just as the light turns green.

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These actions are continuous, as the system recommends specific speeds that vary based on real-time traffic conditions and the state of the traffic light.

In cases where information regarding the leading vehicles as well as information about the following vehicles is available, this enhances the available actions by enabling the ability to provide recommendations also about lane changes.

The reward function for GLOSA is designed to optimise eco-driving performance by minimising delays and emissions. At each time step t , the reward r_i^t for each controlled vehicle i is calculated using a formula that considers both vehicle velocity and emissions:

$$r_i^t = \eta \frac{1}{n} \sum_{i=0}^{n} \left(v_t^i + a 1_{v_t^i < \tau} + \beta e_t^i \right) + (1 - \eta)(v_t^i + a 1_{v_t^i < \tau} + \beta e_t^i) \qquad (14)$$

Where: v_t^i is the velocity of a vehicle i at time t, e_t^i represents the CO_2 emissions of vehicle i at time t, η is a hyperparameter that adjusts the balance between fleet-based and agent-based rewards, a, β, τ are other hyperparameters used to fine-tune the influence of velocity and emissions.

This reward function encourages agents to minimise emissions while optimising travel time. Vehicles receive higher rewards when they travel at speeds that reduce fuel consumption and emissions while also minimising the time spent at traffic signals. Furthermore, the reward can be configured to focus on individual vehicles (agent-based) or across a fleet of vehicles (fleet-based), allowing for flexibility in optimising different traffic scenarios.

The ultimate goal is to maximise cumulative rewards, which reflect an efficient traffic system with reduced delays, fuel consumption, and emissions.

4.1.2 Public transport signal priority

Public Transport Signal Priority (PuT Signal Priority) service involves providing preferential treatment to public transport vehicles, such as buses or trams, as they approach signalised intersections. This service leverages real-time data, including vehicle position, speed, and route, which is transmitted through established communication channels to the traffic signal controller. Upon receiving this data, the signal controller dynamically adjusts the signal timings at downstream intersections to minimise delays for public transport vehicles while maintaining the overall flow of traffic.

Priority is typically granted by either extending the green phase or shortening the red phase (red interruption) for the approaching public transport vehicle, allowing it to pass through the intersection with minimal delay. The system is designed to ensure that priority is granted without compromising road safety or violating any traffic regulations (e.g., compliance with the intergreen timings).

In cases where multiple priority requests are made simultaneously at the same intersection, a first-come-first-served policy is generally applied. However, if multiple requests coincide and can be served by the same traffic signal stage, priority is granted by extending the green phase to accommodate the additional request. This ensures efficient and fair handling of concurrent priority requests, balancing the needs of public transport with overall traffic flow management.

Given the complexities underlined due to the constantly changing traffic conditions, the optimal solution lies in the utilisation of reinforcement learning (RL), which excels in environments that require adaptability and continuous optimisation. RL provides a way to dynamically learn and adjust signal control strategies by interacting with the environment, enabling the system to respond to changing traffic patterns and conditions. For that reason, the solution that will be followed involves the adoption of a multi-agent reinforcement learning (MARL) framework. (Tan, 1993)

Multi-Agent Reinforcement Learning (MARL) is applicable to this problem because it allows for decentralised control and the ability to adjust to fluctuating traffic conditions across numerous signalised intersections without needing pre-existing domain or even network topology related knowledge. MARL agents develop optimal strategies by linking states to actions, making them ideal for complex environments such as traffic systems, where predicting state transitions is particularly difficult. (Tan, 1993)

Within the domain of reinforcement learning in general as well as of that of multi-agent reinforcement learning, an agent learns to behave optimally by interacting with an environment, receiving rewards based on its actions. The goal is to learn an optimal control policy π that maps states to actions to maximise cumulative rewards. In general, RL problems can be modelled as Markov Decision Processes (MDPs), characterized by a set of states S, a set of actions A, and a reward function $T(s, a, s')$. An experience tuple $\langle s, a, s', r \rangle$ indicates the agent's state s, action a, resulting state s', and reward r. The cumulative reward under policy π is defined by the action-value function $Q^{\pi}(s, a)$ as:

$$Q^{\pi}(s, a) = E\left[\sum_{t=0}^{\infty} \gamma^{t} r_{t+s} \mid s_t = s, a_t = a, \pi\right] \qquad (15)$$

where $\gamma \in [0,1]$ is the discount factor for future rewards. The optimal control policy π^* can be obtained if the optimal Q-values $Q^*(s, a)$ are known:

$$\pi^*(s) = \arg\max_{a} Q^*(s, a) \quad \forall s \in S, a \in A \qquad (16)$$

Non-stationarity in RL environments, especially in traffic control, arises when the environment's behaviour evolves over time, impacting the agent's learning process. This requires the agents to constantly adapt, which can lead to performance drops as they must repeatedly adjust their learned policies. Tackling non-stationarity involves implementing strategies that help the agents sustain their performance even as the environment undergoes dynamic changes.

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A framework is introduced for modelling urban traffic with time-varying dynamics. Specifically, an initial baseline urban traffic model is presented based on Markov Decision Processes (MDPs), which includes the formalisation of key MDP elements such as the state space, action set, and reward function. Additionally, the multiagent training scheme employed, known as "Multiagent Independent Q-learning", is described, where each traffic signal agent optimises its policy in non-stationary environments.

The definition of state space strongly influences the agents' behaviour and performance. Regarding the state definition, each traffic signal agent control one intersection and its respective incoming legs. At each time step t, each traffic signal control agent observes a vector s_t, that partially represents the true state of the controlled intersection. A state, in this problem of PuT Signal Priority, could be defined as a vector $s \in \mathbb{R}^{(2+2|P|)}$, as in Equation 3, where P is the set of all green traffic phases, $\rho \in P$ denotes the current green phase , $\delta \in [0, maxGreenTime]$ is the elapsed time of the current phase, $persondelay_i \in [0, \infty]$ is defined as the total delay experienced be drivers/ passengers on the incoming movements of phase i, and $emissions_i \in [0, \infty]$ is defined as the total CO_2 emissions produced by all vehicles on the incoming movements of phase i.

$$s = [\rho, \delta, \mathrm{persondelay}_1, \mathrm{emissions}_1, \dots, \mathrm{persondelay}_{|P|}, \mathrm{emissions}_{|P|}] \qquad (17)$$

The definition provided results in continuous states, but Q-learning traditionally operates with discrete state spaces. Therefore, the states must be discretized after being calculated. Both the $persondelay$ and $emissions$ attributes are discretized into ten levels or bins, evenly distributed. It is important to note that a low level of discretization introduces a form of partial observability, as it can cause distinct states to be interpreted as identical. Additionally, it is assumed that one simulation time step corresponds to five seconds of real-world traffic dynamics. This assumption reflects the fact that traffic signals do not typically change actions every second; instead, actions, such as changes to the current phase of a traffic light, occur at five-second intervals.

In an MDP, at each time step t each agent chooses an action $a_t \in A$. The number of actions, in our setting, is equal to the number of phases, where a phase allows green signal to a specific traffic direction; thus, $|A| = |P|$. Two actions are considered: an agent can either maintain the green signal for the current phase or switch the green signal to another phase; these actions are referred to as "keep" and "change", respectively. There are two constraints on action selection: an agent can only perform the "change" action if $\delta \geq 10\ seconds$ (minGreenTime) and the "keep" action only if $\delta < 50\ seconds$ (maxGreenTime). Additionally, a "change" action triggers a mandatory yellow phase with a fixed duration of 4 seconds. These constraints reflect real-world requirements where a traffic controller must commit to a decision for a minimum amount of time to allow stopped vehicles to accelerate and proceed to their destinations.

The rewards assigned to traffic signal agents in our model are defined as the change in the linear combination of cumulative $persondelay$ and $emissions$ between successive actions. After the execution of an action a_t, the agent receives a reward $r_t \in \mathbb{R}$ as given in the following equation:

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$$r(t) = (W_t + E_t) - (W_{t+1} + E_{t+1}) \qquad (18)$$

Where W_t, E_t and W_{t+1}, E_{t+1} represent the cumulative $persondelays$ and $emissions$ at the intersection before and after executing the action a_t, following equation:

$$\text{Total cost} = \sum_{v \in V_t} \left(w_{v,t} + e_{v,t} \right) \qquad (19)$$

Where V_t is the set of vehicles on roads arriving at an intersection at time step $t, w_{v,t}$ is the total person-delays experience by the drivers/passengers of vehicles v since it entered one of the roads arriving at the intersection (incoming legs) until time step t and $e_{v,t}$ is the total emissions produced by vehicles v since they entered one of the roads arriving at the intersection (incoming legs) until time step t. A vehicle is considered to be waiting if its speed is below 0.1 m/s. Note that, according to this definition, the larger the decrease in cumulative cost, the larger the reward. Consequently, by maximizing rewards, agents reduce the total person-delays and emissions at the intersections, thereby improving the local traffic flow.

Non-stationarity in this scenario is addressed by employing Q-learning within a multiagent independent training framework (Tan, 1993), where each traffic signal functions as a Q-learning agent with its own Q-table, local observations, actions, and rewards. This method enables each agent to learn an individual policy based on its local observations, allowing policies to differ between agents as each one updates its Q-table using only its own experience data. In addition to facilitating different behaviours across agents, this decentralized approach helps avoid the curse of dimensionality that would arise in a centralized training system.

4.1.3 Max-pressure traffic signal control

Max-pressure Traffic Signal Control (Max-pressure TSC) is an advanced and decentralized traffic signal control strategy designed to optimize overall network throughput by dynamically adjusting signal timings based on real-time traffic conditions at each intersection. Unlike traditional traffic control systems that rely on centralized control with predefined timings or require complex computational power to synchronize intersections, Max-pressure TSC operates based on local information, making it highly scalable and adaptable to different traffic demands. The core concept behind Max-pressure TSC is to allocate green signal time to the lanes or directions experiencing the most “pressure”, where pressure is determined by the difference in vehicle queue lengths between upstream and downstream intersections.

Max-pressure TSC measures pressure at an intersection by calculating the difference between the queue lengths of vehicles waiting at a particular signal phase (incoming traffic) and the available space or queue lengths at downstream intersections (outgoing traffic). The system then dynamically adjusts the signal phases by prioritising movements that relieve the greatest pressure. In practical

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terms, Max-pressure TSC continually evaluates traffic in all directions and assigns green phases to the direction with the highest pressure, effectively reducing network congestion. (Sun & Yin, 2018)

Max-pressure Traffic Signal Control (TSC) operates as a decentralised system, relying solely on local information for making control decisions. Each intersection functions independently, using real-time data about vehicle queues to allocate signal phases optimally. This decentralised structure allows the system to dynamically adapt to changing traffic conditions without requiring the full network traffic state. As a result, Max-pressure TSC simplifies deployment, reduces computational overhead, and is highly scalable, making it suitable for large and complex urban traffic networks. This flexibility makes it particularly effective for managing traffic in expansive urban areas with diverse traffic flows. (Sun & Yin, 2018)

Max-pressure TSC can be further enhanced by integrating reinforcement learning (RL), enabling the system to continuously learn and improve its decision-making process over time. RL agents at each intersection can learn the optimal way to allocate green time based on historical traffic data and real-time conditions. By interacting with the environment and receiving rewards based on the efficiency of traffic flow (e.g., reduced delay, minimised queue lengths), RL-based Max-pressure control can develop policies that better adapt to peak-hour traffic, unforeseen congestion, and other variable conditions.

One of the key challenges with traditional Max-pressure TSC is the frequent phase switching, which can lead to inefficiencies such as start-up delays when switching signals too frequently. This frequent switching can also lead to driver confusion and increase fuel consumption due to repeated acceleration and deceleration. To address this issue, modifications have been proposed, such as introducing a minimum green time to limit the frequency of phase changes, ensuring that each signal phase stays active long enough to allow vehicles to clear the intersection.

The state space in the Max-pressure Traffic Signal Control (TSC) system captures critical traffic-related variables at each signalised intersection. The observed state at any given time includes:

- Queue lengths: The number of vehicles waiting in the queue on each approach to the intersection. The queue length for each movement (from link l to link m) is denoted as $q_{l,m}(t)$ at time t. This queue information is used to estimate pressure and guide signal phase decisions.
- Flow proportions: The proportion of vehicles on each link that are expected to continue onto the next intersection. This is represented as $p_{l,m}(t)$ capturing how much of the traffic flow is directed toward the downstream links.
- Arrival rates: For entry links, the exogenous vehicle arrival rate $a_l(t)$ at time t is also part of the state. For internal links (not entry points), the arrival rate depends on the upstream queue dynamics and the number of vehicles leaving upstream intersections.

These components of the state space enable the system to make real-time assessments of traffic conditions, helping to optimize signal phase decisions.

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The action set in Max-pressure TSC refers to the decision of which signal phase to activate at each time step. Each phase corresponds to a particular movement through the intersection, allowing vehicles from certain directions to pass through. The set of possible actions A includes:

- Selecting a phase: At each time step t, the system selects a phase $s(t)$ from the set of available phases P_i for each intersection i. Each phase $s(t)$ serves a particular movement, allowing vehicles to travel from one link to another (e.g., from link l to link m).
- Green time allocation: The system allocates green time to the chosen phase, ensuring that vehicles are allowed to move based on their queue lengths and downstream conditions.

The system is designed to make decisions in real-time, based on the current state, without requiring predetermined cycle lengths or fixed timings, which distinguishes it from traditional traffic signal control strategies.

The reward function in Max-pressure TSC is designed to maximise overall network throughput by minimising congestion. The pressure associated with each phase $s(t)$ is defined as the difference between the queue length on the current link and the expected queue length on the downstream link. The pressure for a given movement from link l to link m is calculated as:

$$w_{l,m}(t) = q_{l,m}(t) - \sum_{n \in O_m} p_{m,n}(t) q_{m,n}(t) \qquad (20)$$

Where: $q_{l,m}(t)$is the queue length on link l at time t, $p_{m,n}(t)$ is the flow proportion for the movement from link m to link n, $q_{m,n}(t)$ is the queue length of the downstream link m.

The pressure for each phase is then aggregated for all movements served by that phase. The goal is to select the phase with the maximum pressure, as this will help relieve the most congested movements and reduce overall queue lengths. The system iterates through all possible phases and selects the one that maximizes the pressure:

$$s * (t+1) = arg \max_{s \in P_i} \sum_{(l,m) \in s} w_{l,m}(t) \qquad (21)$$

This reward function ensures that the system prioritizes movements that will reduce the most congestion, dynamically adapting to changing traffic conditions. The system is also designed to ensure network stability, as it minimises the possibility of gridlock by balancing pressures across the entire traffic network.

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4.2 Implementation approach

This section provides an overview of the implementation approach that will be followed for the three previously described measures: Green Light Optimal Speed Advisory (GLOSA) – Eco-driving, Public Transport Signal Priority (PuT Signal Priority), and Max-pressure Traffic Signal Control (Max-pressure TSC).

As mentioned earlier, the implementation and assessment of both the GLOSA – Eco-driving and PuT Signal Priority services will be based on the adoption of a multi-agent reinforcement learning (MARL) framework. This approach allows for decentralized decision-making, enabling individual agents to interact with the traffic environment and optimize their actions based on real-time traffic conditions.

For the evaluation of the MARL framework in both GLOSA – Eco-driving and PuT Signal Priority services, an existing simulation environment, SUMO-RL, will be extended to model urban traffic with varying degrees of non-stationarity, including fluctuating traffic patterns. Multiple agents will be trained and tested to assess their performance under these conditions. SUMO-RL (Alegre et al., 2021) provides an accessible interface to set up Reinforcement Learning (RL) environments within SUMO (Lopez et al., 2018), specifically for Traffic Signal Control. The platform supports MARL and can be customized with new state space and reward function definitions to evaluate the performance of these services in various urban scenarios. The architecture of the adopted MARL framework is illustrated in Figure 5.

In addition to the SUMO-RL environment, the GLOSA – Eco-driving service will be implemented and tested using the IntersectionZOO simulation platform (V. Jayawardana, B. Freydt, A. Qu, C. Hickert, Z. Yan, C. Wu, n.d.). IntersectionZOO offers a detailed and customizable traffic simulation environment that can effectively model the complexities of urban traffic systems, including signalized intersections and variable traffic volumes. The platform's capabilities will be extended to enable the application of GLOSA – Eco-driving across multiple signalized intersections within the same network, allowing the assessment of the service in more complex urban traffic environments. This expansion will provide insights into how GLOSA can enhance traffic efficiency and reduce emissions across larger urban networks.

Finally, the Max-pressure Traffic Signal Control (Max-pressure TSC) will also be integrated into the overall system. The Max-pressure TSC approach dynamically adjusts signal timings by evaluating real-time queue lengths at intersections and prioritizing movements with the highest pressure to optimize traffic flow and minimize congestion. Its decentralized nature makes it compatible with the MARL framework and suitable for large-scale urban networks. The combination of these three services within the MARL framework will enable an advanced, adaptive, and real-time traffic management solution that improves network-wide traffic flow, reduces delays, and promotes eco-friendly driving behaviour. (Sun & Yin, 2018)

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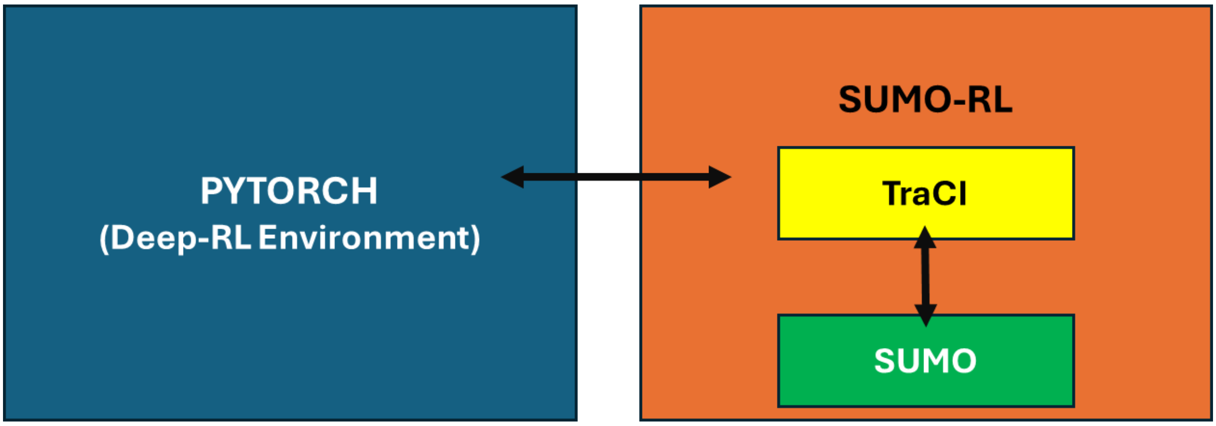
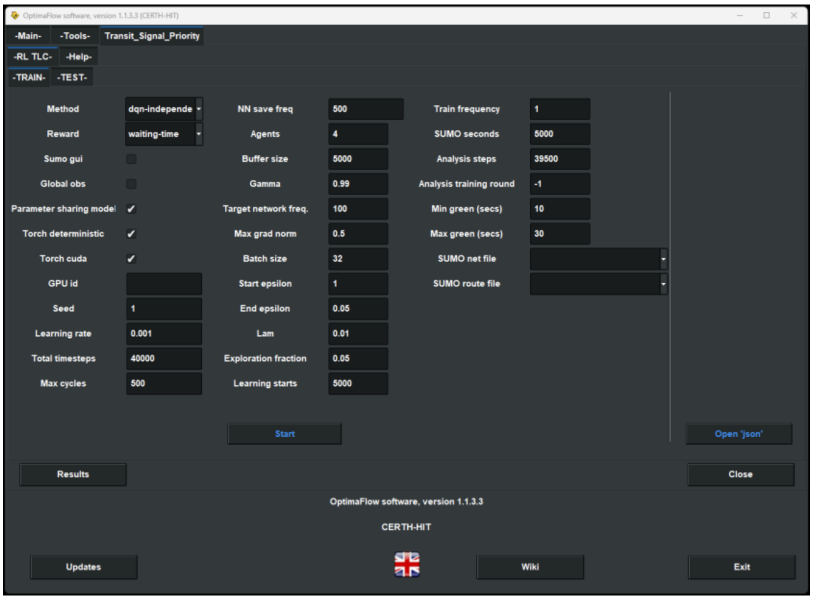


Figure 5: The architecture of the MARL framework.

The experiments will involve training RL agents in the SUMO simulation environment and evaluating their performance in terms of average person delays and emissions.



Method	dqn-independe	NN save freq	500	Train frequency	1
Reward	waiting-time	Agents	4	SUMO seconds	5000
Sumo gui	☐	Buffer size	5000	Analysis steps	39500
Global obs	☐	Gamma	0.99	Analysis training round	-1
Parameter sharing model	☑	Target network freq.	100	Min green (secs)	10
Torch deterministic	☑	Max grad norm	0.5	Max green (secs)	30
Torch cuda	☑	Batch size	32	SUMO net file	
GPU id		Start epsilon	1	SUMO route file	
Seed	1	End epsilon	0.05		
Learning rate	0.001	Lam	0.01		
Total timesteps	40000	Exploration fraction	0.05		
Max cycles	500	Learning starts	5000		

OptimaFlow software, version 1.1.3.3
CERTH-HIT

Figure 6: Custom software platform developed for instantiating SUMO-RL and training the MARL agents.

A dedicated simulation platform will be developed to facilitate the training of the RL agents (**Error! Reference source not found.**) and expedite the execution of simulations with and without the GLOSA – Eco-driving service, with and without the PuT Signal Priority service, with and without the Max-Pressure TSC (**Error! Reference source not found.**). This platform will enable users to define values for the training parameters of the RL agents and select optimisation objectives for running the simulations.

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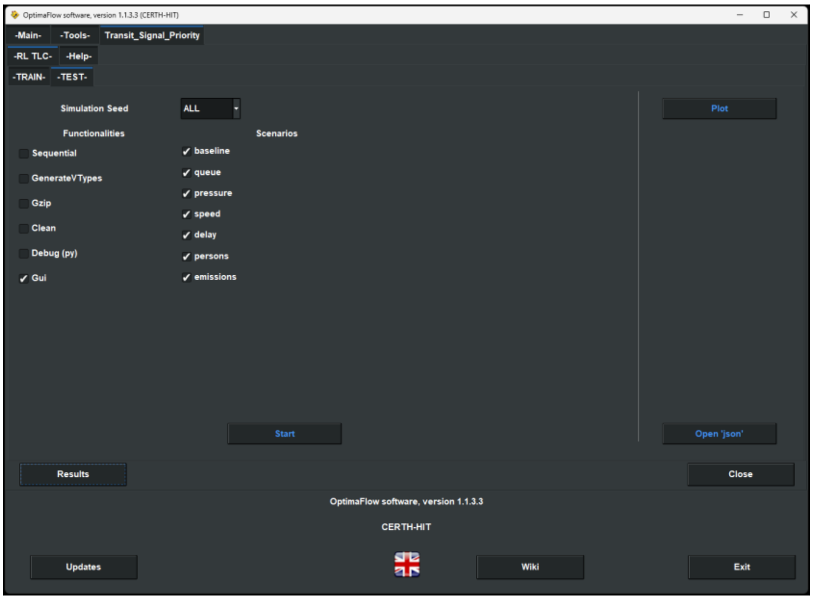

Simulation Seed ALL

Functionalities
☐ Sequential
☐ GenerateVTypes
☐ Gzip
☐ Clean
☐ Debug (py)
☑ Gui

Scenarios
☑ baseline
☑ queue
☑ pressure
☑ speed
☑ delay
☑ persons
☑ emissions

OptimaFlow software, version 1.1.3.3

CERTH-HIT

Figure 7: Custom software platform for executing the MARL-based TSP algorithm in SUMO simulations.

Performance metrics, such as average delay per vehicle type, the number of stops made by vehicles, overall network throughput, average vehicle speed across the network, and total emissions produced, will be employed to evaluate the effectiveness of the agents in optimizing traffic flow for all vehicles. These metrics will help assess how well the agents balance the objectives of reducing delays and emissions, providing efficient priority for public transport, improving eco-driving behaviours, and minimizing congestion. The evaluation will ensure that these optimisations enhance overall traffic efficiency without negatively impacting other road users or degrading air quality.

5 Social Routing

5.1 Formulation of the optimisation problem

The Social Routing Optimisation Problem aims at leveraging classical and novel ITS tools and technologies such as Variable Message Signs (VMS), Cooperative Intelligent Transport Systems (C-ITS) through Roadside Units (RSUs), and Navigation Apps to coordinate re-routing strategies with the objective of optimising traffic flow, reducing congestion, lowering emissions, and ensuring fairness in travel times for all users.

This optimisation problem seeks to identify the most effective re-routing strategies that should be recommended to users through VMSs, RSUs, and navigation apps in order to improve network performance according to predefined KPIs.

A critical focus is on understanding and analysing the compliance/adoption rates of drivers—specifically, the likelihood that they will adhere to the route suggestions provided by VMS, RSUs, or navigation apps. This compliance rate reflects the percentage of drivers who will follow these recommendations, influenced by factors such as user habits, trip purpose, time of day, etc. Although these elements will not be directly controlled by this optimisation module, it will use a component that will be designed specifically for this purpose in WP4 that will estimate the acceptance rates of the suggested routes. The goal is to find coordinated re-routing strategies that minimise travel delays, reduce environmental impact, and ensure that no group of users is disproportionately affected by re-routing decisions.

Let us define the three tools that will be used to suggest rerouting options to the users:

- Variable Message Signs (VMS): Electronic displays located on highways that suggest alternate routes to drivers based on current traffic conditions. Each VMS has a predefined set of routes it can recommend to drivers, ensuring that these suggestions are based on real-time data.
- Roadside Units (RSUs): Infrastructure that facilitates communication between vehicles and the transportation network, providing real-time route suggestions. RSUs possess a set of predefined routes that can be communicated to drivers. This ensures consistency in the information provided across the network.
- Navigation Apps: Applications like Google Maps or Waze that utilise user-specific data (origin, destination, etc.) to offer re-routing options based on traffic patterns. Users with similar origins and destinations will share common predefined routes, and the system can select the percentage of users to suggest alternative routes, thereby allowing for targeted re-routing strategies.

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While each VMS and RSUs unit can provide route recommendations independently, a coordination mechanism is in place to ensure that these suggestions do not conflict. This system evaluates real-time traffic conditions in the simulation and prioritizes recommendations based on various factors, such as congestion levels and user compliance rates. By integrating these suggestions, the system aims to enhance user adherence and improve overall traffic flow.

The objective of this optimisation process is to find the optimal combination of strategies for VMS, RSUs, and navigation apps. This includes:

- Determining which routes should be recommended by each VMS and RSU.
- Assigning a percentage of users from navigation apps with similar origins and destinations to specific routes.
- Evaluating the compliance of users with these recommendations and simulating the resulting routes to assess how well these strategies reduce congestion and emissions and ensure user fairness.

The routes between each origin-destination (OD) pair are defined as follows:

Let $O = \{O_1, O_2, O_3, \ldots, O_N\}$ represent the set of origins and $D = \{D_1, D_2, D_3, \ldots, D_M\}$ the set of destinations. For each origin-destination pair (O_i, D_j), there is a set of possible routes $R_{O_iD_j} = \left\{r^1_{O_iD_j}, r^2_{O_iD_j}, \ldots, r^{k_{O_iD_j}}_{O_iD_j}\right\}$, where $k_{O_iD_j}$ represents the maximum number of routes that exist between the origin O_i and destination D_j.

VMS and RSU provide predefined route options at certain locations in the network. Each device has a set of possible routes it can suggest to users:

- $VMS_i \rightarrow \left\{r^1_{VMS_i}, r^2_{VMS_i}, \ldots, r^{k_{VMS_i}}_{VMS_i}\right\}$
- $RSU_i \rightarrow \left\{r^1_{RSU_i}, r^2_{RSU_i}, \ldots, r^{k_{RSU_i}}_{RSU_i}\right\}$

Let N_{VMS} represent the total number of VMS available in the network, and N_{RSU} denote the total number of RSUs available in the network. Each VMS_i or RSU_i unit can recommend routes independently at a specific location of i. For each VMS_i, a one-hot encoded vector $\boldsymbol{x_{VMS_i}} = \left\{r^1_{VMS_i}, r^2_{VMS_i}, \ldots, r^{k_{VMS_i}}_{VMS_i}\right\}$, where $r^j_{VMS_i}$ is a binary variable that indicates whether the j-th route is assign to the i-th VMS ($r^j_{VMS_i} = 1$ o not $r^j_{VMS_i}$ = 0. Since only one route can be assign at a time to a VMS, the vector x_{VMS_i} use a one-hot enconding scheme where only one element is 1, representing the chosen route, and all others are 0). Similarly, for RSU_i, the decision vector $\boldsymbol{x_{RSU_i}}$ is defined in the same manner. This approach allows the model to specify a unique recommended route for each VMS or RSU based on the position provided.

For users traveling from O_i to D_j, the continuous variable $p_{O_iD_j}^{k_{O_iD_j}}$ represents the percentage of users assigned to the k-th route by navigation apps, where k can take values from 1 to $k_{O_iD_j}$. These percentages are also independent of the VMS and RSU route selections.

Let $\boldsymbol{X}$ be the decision variable that encompasses the one-hot encoded route selection vectors for all VMS, denoted as $\boldsymbol{x_{VMS}} = \{x_{VMS_1}, \dots, x_{VMS_{N_{VMS}}}\}$. It also includes the one-hot encoded route selection vectors for all RSUs, represented as $\boldsymbol{x_{RSU}} = \{x_{RSU_1}, \dots, x_{RSU_{N_{RSU}}}\}$. Additionally, this decision variable incorporates the continuous percentages of users assigned to each route between OD pairs, expressed as $\boldsymbol{p_{OD}} = \{p_{O_1D_1}^{\square}, \dots, p_{O_ND_M}^{\square}\}$.

The objective function of the optimisation model aims to minimize the following weighted sum, which captures traffic congestion (C), emissions (E), and user fairness (F):

$$\min_{\boldsymbol{X}} Z(\boldsymbol{X}) = w_1 C(\boldsymbol{X}) + w_2 E(\boldsymbol{X}) + w_3 F(\boldsymbol{X}) \qquad (22)$$

$$s.t. \qquad \sum_{k=1}^{k_{O_iD_j}} p_{O_iD_j}^{k} = 1\,, \qquad \forall i,j \qquad (23)$$

$$\sum_{k=1}^{k_{VMS_i}} x_{VMS_i}^{k} \leq 1\,, \qquad \forall k \qquad (24)$$

$$\sum_{k=1}^{k_{RSU_i}} x_{RSU_i}^{k} \leq 1\,, \qquad \forall k \qquad (25)$$

where C is the level of congestion experienced on the network, E is the amount of emissions generated by the traffic. F, the user fairness, is defined as the absolute difference between the travel times of re-routed users and non-re-routed users. These metrics in formulation (22) are outputs from a transportation simulator that evaluates the configuration of VMS, RSUs, and the assigned probabilities. The weights $w1, w2, w3$ are determined based on the preferences of the user. This approach ensures that re-routing strategies do not disproportionately impact any specific group of users, promoting fairness in travel times.

The optimisation problem is subject to three key constraints that ensure the effective allocation of routes and resources. First, constraint (23) mandates that the total percentage of users $\boldsymbol{p_{O_iD_j}}$ assigned to routes between each OD pair must sum to 1, ensuring that every user is accounted for in the routing strategy. Next, constraint (24) restricts each $\boldsymbol{x_{VMS_i}}$ to suggest only one route at a time, thereby preventing conflicting recommendations. Similarly, constraint (25) enforces that each $\boldsymbol{x_{RSU_i}}$ can also suggest only one route, maintaining clarity in routing instructions.

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5.2 Implementation approach

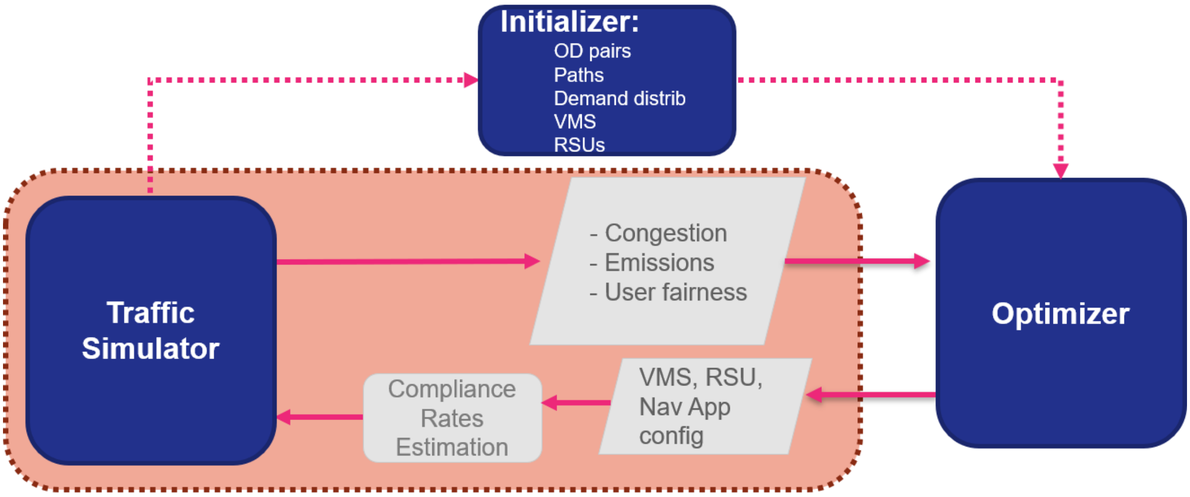

Figure 8: Schematic diagram for the social routing optimisation problem

The implementation of the social routing optimisation problem is structured around a data-driven optimisation framework that combines traffic simulation with an optimisation algorithm to generate and evaluate alternative re-routing strategies. The main objective is to minimize congestion, reduce emissions, and ensure fairness in travel times across users. The process begins with the Initializer, which provides essential inputs such as origin-destination OD pair data, paths, locations of VMS, RSUs, and demand distribution. This data is collected and pre-processed from various sources, including real-time and historical traffic data. Once the data is processed, it is fed into the optimisation model, where the Optimizer seeks the best configuration of routes and user distributions. The decision variables represent the distribution of drivers across available routes, the recommendations made by VMS, and the signals from RSUs. Figure 8 illustrates this overall process, highlighting the roles of each block in the framework.

The optimisation model is formulated with an objective function that is a weighted combination of three key performance metrics: traffic congestion, total emissions, and user fairness. Each metric is assigned a weight based on its relative importance, allowing the optimisation process to prioritise objectives like congestion reduction, emissions minimisation, or user fairness, depending on the scenario. The decision variables include discrete choices for the recommended routes from VMS and RSUs, as well as continuous variables representing the distribution of users across different paths suggested by navigation applications.

The Traffic Simulator is employed to simulate the effects of different routing strategies on traffic flow, emissions, and user fairness. During each iteration, the simulator calculates KPIs that are fed into the optimisation algorithm, helping it refine its search for optimal re-routing strategies. This process involves iteratively simulating route assignments and adjusting the distribution of users across available paths. After each iteration, the generated solutions are evaluated using a traffic

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simulation model, which assesses performance by calculating key metrics such as congestion, emissions, and fairness in travel times. These performance indicators are then fed back into the optimisation process, guiding it towards improved solutions until the stopping criterion is reached.

The simulation process also accounts for variations in driver behaviour and compliance rates, which can fluctuate depending on different factors. To address this challenge, the simulation model incorporates multiple compliance scenarios, enabling the optimisation process to evaluate solutions under different levels of user adherence to routing recommendations. This ensures that the optimisation process accommodates uncertainty and variability in real-world conditions.

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6 Roadworks planning

Roadworks are essential for infrastructure maintenance and improvement but can also be highly disruptive. Managing these projects in urban areas presents a complex challenge that affects daily life, economic activity, and the environment. Poorly coordinated or improperly timed roadworks often lead to severe traffic congestion, increased vehicle emissions, and delays in PT services (Vallati & Chrpa, 2020). As traffic volumes continue to grow, cities must schedule essential maintenance and upgrades in a way that minimises disruption. The Roadworks Scheduling Optimisation Problem addresses this need by creating efficient schedules that balance these competing priorities (Li & Fan, 2021).

This scheduling issue can be understood as a scheduling problem in which multiple roadworks must be planned and executed within a limited timeframe. Each roadwork project is divided into several sequential phases that must be completed within a designated time horizon. The objective is to develop schedules that ensure the timely completion of each roadwork phase, assuming a limited number of simultaneous active roadworks. This requires balancing conflicting priorities, such as minimising disruptions to traffic and PT services (Vallati et al., 2019).

In the context of this optimisation, let N_R denote the total number of roadworks projects, represented as $\{R_1, R_2, \ldots, R_{N_R}\}$, where R_i refers to the i-th project. Each roadwork R_i is composed of a sequence of phases $\{p_1^i, p_2^i, \ldots, p_{n_i}^i\}$, where n_i represents the number of phases in R_i and j is the phase index within that project.

The vector $\boldsymbol{st_{R_i}} = \{st_{p_1^i}, \ldots, st_{p_{n_i}^i}\}$ consists of the start times $st_{p_j^i}$ for each phase p_j^i in roadwork R_i, where j varies from 1 to n_i. The decision variable $\boldsymbol{X}$ is defined as the vector of the start times for all phases across all roadwork projects. Thus, $\boldsymbol{X}$ can be expressed as:

$$\boldsymbol{X} = \left\{\boldsymbol{st_{R_1}}, \boldsymbol{st_{R_2}}, \ldots, \boldsymbol{st_{R_{N_R}}}\right\}$$

The optimisation process aims to minimise negative impacts on the urban network, evaluated through three KPIs: traffic congestion (C), vehicle emissions (E), and PT travel time delays (T_{PT}). The total impact cost is calculated using a weighted sum of these KPIs to ensure that roadworks are completed efficiently:

$$\min_{\boldsymbol{X}} I(\boldsymbol{X}) = w_1 C(\boldsymbol{X}) + w_2 E(\boldsymbol{X}) + w_3 T_{PT}(\boldsymbol{X}) \qquad (26)$$

$$\begin{aligned} s.t. \quad & st_{p_j^i} \geq st_{p_{j-1}^i} + d_{p_{j-1}^i}, && \forall i, \forall j > 1 && (27) \\ & st_{p_{n_i}^i} + d_{p_{n_i}^i} \geq D_i, && \forall i && (28) \\ & |A(t)| \leq M, && \forall t && (29) \end{aligned}$$

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where w_1, w_2 and w_3 are weights determined based on the preferences of the user. These weights reflect the relative importance of congestion, emissions, and PT delays.

The overall objective is to find a schedule that minimises the total weighted impact $I(\boldsymbol{X})$ in formulation (26), while ensuring that all roadwork phases meet their deadlines and do not exceed the allowed number of simultaneous active roadworks, denoted as M. The optimisation model aims to develop schedules that facilitate the timely completion of each phase of the roadworks while balancing conflicting priorities, such as minimising disruptions to traffic and PT.

To ensure the feasibility of work schedules, the planning process must adhere to various operational and logistical constraints. Each phase of a roadwork project must begin only after the previous phase has been completed, adhering to sequentially; that is in constraint (27), where $d_{p_{j-1}^i}$ is the duration of the previous phase $(j-1)$ of roadwork R_i. Additionally, each project must be completed by a predetermined deadline D_i, ensuring that constraint (28), where $p_{n_i}^i$ is the last phase of the roadwork R_i. Furthermore, the number of active roadworks at any given time must not exceed a predefined maximum limit M (i.e., constraint (29)), where $A(t)$ represents the set of active roadworks at time t.

6.1 Implementation approach

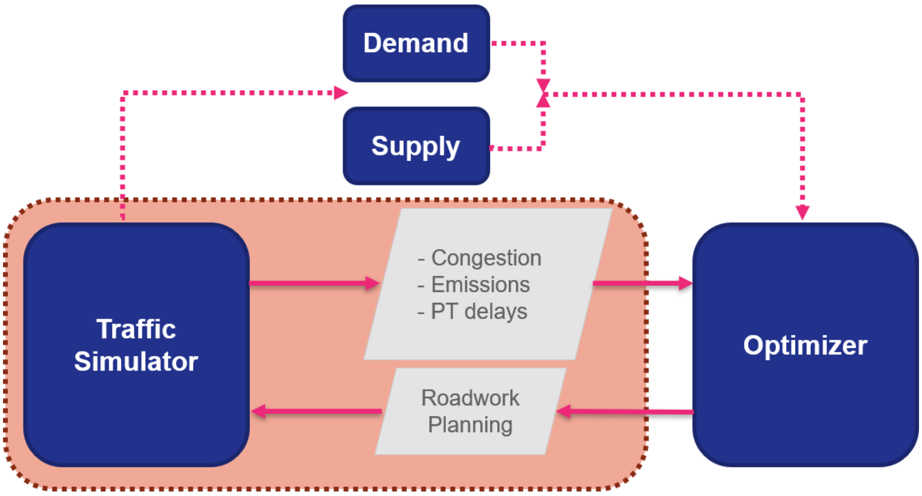

Figure 9: Schematic diagram for the roadworks scheduling optimisation problem

The implementation of the roadworks scheduling optimisation problem is structured around a data-driven optimisation framework that combines traffic simulation with an optimisation algorithm to generate and evaluate alternative scheduling strategies for roadwork projects. The main objective is to minimize traffic congestion, reduce vehicle emissions, and limit delays in PT across the urban network. The process starts with the collection and pre-processing of key data, such as real-time and historical traffic information, roadwork locations, phase durations, and expected traffic flow.

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Once this data is processed, it is integrated into the optimisation model, where the decision variables represent the scheduling and timing of roadwork phases. The demand and supply blocks form the core inputs for the optimisation process. The Demand block contains the OD matrix, which captures traffic flows, while the Supply block defines the specific road closures and road capacity limitations of the roadworks.

The optimisation model is formulated with an objective function that is a weighted combination of KPIs: traffic congestion, total emissions, and PT delays. Each KPI is assigned a weight based on its relative importance, allowing the optimisation process to prioritise objectives accordingly. The decision variables include start times for each phase of the roadworks, ensuring that the scheduling strategy minimises the overall impact on the urban network.

The optimiser iteratively adjusts the roadwork schedules and passes the proposed plans to the traffic simulator, which evaluates the performance of each schedule by calculating the relevant KPIs. In each iteration, the simulator provides feedback on metrics such as congestion, emissions, and PT delays, which is then used to refine the optimisation. This process continues until an optimal or satisfactory schedule is identified or a stopping criterion is met.

Operational constraints, such as maintaining the sequence of work phases, adhering to project deadlines, and limiting the number of simultaneous roadworks, are incorporated into the model to ensure feasibility. These constraints help balance conflicting priorities, such as minimising traffic disruption while ensuring the timely completion of the roadworks.

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7 Automatic recommendation of interventions

7.1 Formulation of the optimisation problem

Traditional traffic management methods often rely on static rules or human intervention, which are not always optimal, especially in dynamic, complex environments where many factors can change from one day to another or throughout the day.

In addition, cities must balance various objectives: minimising travel delays, reducing emissions, and enhancing safety. The complexity of traffic networks, the unpredictability of demand, and the variability of possible incidents make it challenging to create universal traffic management strategies. Therefore, there is a growing interest in developing automatic systems that can recommend effective, context-specific interventions to mitigate traffic disturbances.

The approach proposed in SYNCHROMODE relies on machine learning and optimisation techniques to create a system capable of recommending traffic management strategies tailored to specific road network disruptions. Below are the key steps of the model:

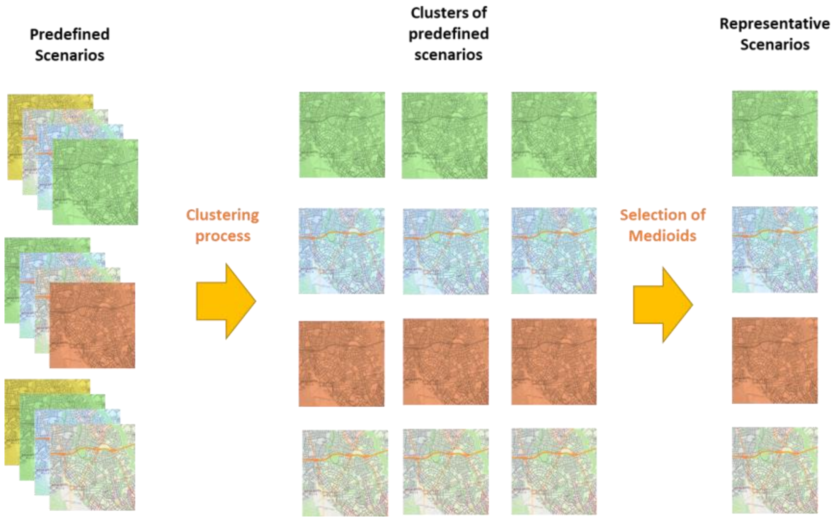

Figure 10 Schema for scenario definition and clustering

1. **Scenario Definition and Clustering (see Figure 10):**

First, a set of predefined scenarios is developed, representing different patterns of the transport network status. These scenarios can include partial or complete closures caused by roadworks, accidents, or temporary events.

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These predefined scenarios are analysed and clustered into groups. Clustering methods, such as k-means or hierarchical clustering, can be used to identify similarities between scenarios. This process reduces the complexity of the problem by focusing on representative scenarios - those that encapsulate the typical traffic patterns caused by road disruptions in each cluster.

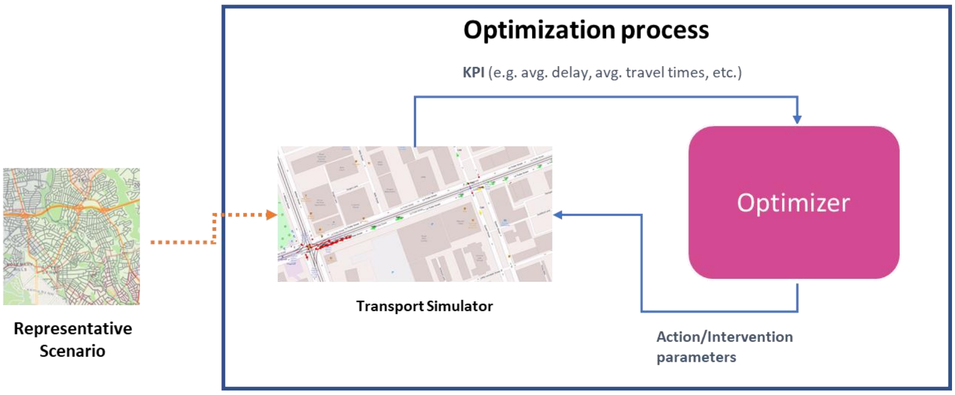

Figure 11 Schema for Optimisation for Representative Scenarios

2. **Optimization for Representative Scenarios (see** Error! Reference source not found.**):**

Once the representative scenarios are identified, optimisation methods are applied to design specific interventions. These interventions include:

- Coordinate re-routing strategies using the social routing optimisation method.
- Traffic control measures by the optimisation of traffic control plans for the specified representative scenario.

The outcome is a set of tailored re-routing strategies and traffic control plans that are designed for each representative day.

With the previous outcome, a dataset that maps the predefined representative scenarios to the associated re-routing strategies and traffic control plans is created.

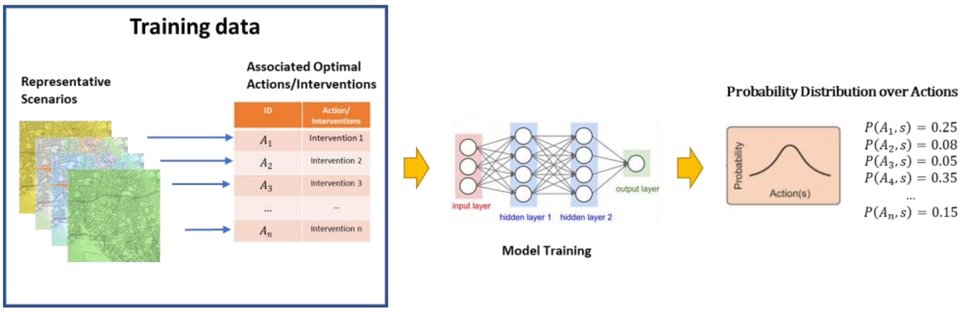

Figure 12 Schema for Training the Machine Learning Model for automatic recommendation of interventions

3. **Training the Machine Learning Model for automatic recommendation of interventions (see** Error! Reference source not found.**):**

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Then, the ML classifier model is trained to learn the relationship between the characteristics of the transport network status and disruptions (input features such as road closure locations, traffic volumes, delay times, etc.) and the optimal interventions (output labels such as recommended re-routing paths and traffic signal settings).

The model will learn the probability distribution of the most suitable intervention over the available interventions.

7.2 Implementation approach

The implementation of the proposed model in SYNCHROMODE for the automatic recommendation of interventions is a proof of concept. The objective is to test it in a limited environment and with a pre-defined number of scenarios. Moreover, the system is not intended to work in real-time but to recommend actions or interventions for specific scenarios. In this way, we will show how this type of system could work, and in the following deliverables, depending on the results obtained, we will discuss how this type of system could be scaled up in the future to have automatic intervention recommendation systems in real-time.

That said, we now describe how the automatic intervention recommendation system would be implemented once we have the machine learning model resulting from step 3 described in the previous section. A schema of this implementation is shown in **Error! Reference source not found.**.

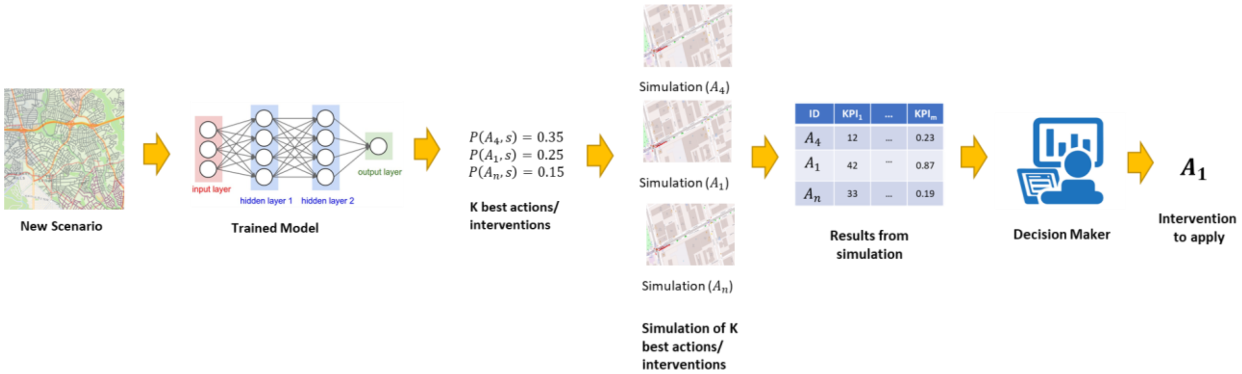

Figure 13 Schema of the implementation of the automatic recommendation of interventions

Once trained, the machine learning model described above can be used to recommend specific re-routing strategies and traffic control plans for new scenarios that were not included in the original set of predefined scenarios. This enables the system to provide suggestions for traffic management interventions for new scenarios, leveraging its understanding of network patterns of similar scenarios.

As a proof of concept, this module will be applied to the optimised scheduling of roadworks resulting from the module described in Section **Error! Reference source not found.Error! Reference source**

not found.. Concretely, this module will be applied to estimate the best coordinated re-routing strategies and traffic control plan for each day on which scheduled roadworks are active.

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8 Conclusions

The optimisation models for transport network management outlined in this document represent the main outcome of Task 5.2 of the SYNCHROMODE project. This deliverable provides an overview of the mathematical models developed for six key optimisation challenges: Synchronization of PT and DRT, FoT, Advanced C-ITS and Traffic Signal Control Measures, Social Routing, Roadworks Planning, and Automatic Recommendation of Interventions. These models are designed to enhance operational efficiency, reduce emissions, and improve user experience within urban transport systems.

In addressing the synchronisation of PT and DRT, the objective is to optimise DRT deployment to enhance coverage in low-service areas, thereby ensuring seamless connections between DRT services and PT options. The models developed aim to effectively allocate resources to serve more passengers while minimising operational costs and energy consumption. The integration of parcel delivery within PT systems through the FoT model focuses on leveraging existing infrastructure to meet urban freight demands without compromising passenger service quality.

Moreover, the advanced C-ITS and traffic signal control measures focused on three strategies to enhance traffic flow and reduce delays at intersections, such as GLOSA, Public Transport Signal Priority and Max-pressure Traffic Signal Control. The Social Routing model aims to coordinate simultaneous different rerouting strategies through VMS, RSU and Navigation apps to optimise traffic flow, reduce congestion, lower emissions, and ensure fairness in travel times for all users. The Roadworks Planning aims to optimise schedules in such a way that ensures the timely completion of each roadwork phase, assuming a limited number of simultaneous active roadworks, while minimising traffic congestion, emissions and PT delays.

Finally, the Automatic Recommendation of Interventions showed a three-phase approach that leverages unsupervised and supervised machine learning techniques to develop models that can provide tailored rerouting strategies and traffic control plans for specific transport network conditions.

For each of the optimisation challenges discussed, we have provided a brief description, mathematical formulation, and schematic integration with transport simulation platforms. This foundational work sets the stage for Task 5.3, where various mathematical approaches and methods will be explored to address these optimisation problems further.

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