Fleet and traffic management systems
for conducting future cooperative mobility

D3.2 Specification and initial version of techniques for dynamic optimization and network load-balancing

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EXECUTIVE SUMMARY

This deliverable, which is intricately linked to Task 3.3 on "Network Load Balancing" is a critical milestone in the Grant Agreement's overarching goal of using Connected and Autonomous Vehicles (CAVs) to redefine traffic management, optimize transport network performance, and address load balancing and dynamic optimization challenges. The study gives a complete update on the domain's cutting-edge solutions, as well as a detailed description of the joint efforts achieved thus far.

The background section highlights the importance of socially desirable routing in ensuring optimal system performance, establishing the framework for the joint initiative's primary focus—the refinement of social routing algorithms. This change, intended to direct travellers toward socially desired routes, is considered the key to establishing network load balancing over several spatiotemporal scales. The collaborative effort involves the enhancement of the social routing model, the multi-modal integration, the tailored pre-trip route recommendations, and the introduction of smart algorithms and machine learning applications.

Fleet optimization strategies and system-optimized routing techniques for fleet vehicles are investigated, and AI algorithms for optimizing CAV scheduling and travel routes are developed. The process begins with a careful state-of-the-art review that covers essential areas such as signal vehicle coupling control, social routing dynamics, prediction models, and optimization techniques. The following sections provide a thorough review of tasks completed in the past months, demonstrating the depth and breadth of the collective effort. Finally, this deliverable exemplifies a collaborative initiative poised to shape the future of transportation network optimization through the integration of emerging technologies and strategic insights, demonstrating a commitment to innovation and excellence in the transportation domain.

Keywords: Network Load Balancing, Connected Autonomous Vehicles (CAVs), Social routing, Demand Responsive Transport, Demand Prediction

1 INTRODUCTION

This deliverable is tied to Task 3.3 “Network Load Balancing” problems and hence to the tasks’ outcomes. As per the Grant Agreement, this task intends to create cutting-edge technologies to assist traffic management and utilize the potential of CAVs to better balance demand and supply, optimize the overall transport network's performance, and assist the network in recovering from small traffic incidents. This deliverable incorporates state-of-art updates on the existing solutions in transport network load balancing and dynamic optimization. It also provides an update on the work done to date regarding the identified problems related to traffic network load balancing and dynamic optimization. The objectives for this deliverable have been met completely.

1.1 Background

Network load balancing tries to rebalance demand throughout the network in order to improve system performance and, as a result, the mobility of products and people. Whilst the majority of network agents are primarily concerned with their own utility when making decisions, societal objectives frequently conflict with individual ones, necessitating central coordination to improve the mobility network. Centrally controlled traffic management solutions based on route guidance can both direct or encourage mobility system actors toward socially desirable routes. Overlooking user demands and responses frequently results in unfulfilled strategies. Guidance techniques should not only direct users toward socially beneficial routes based on present and future network conditions but should also factor in the consequences of guidance in forecasts. Choice dynamics occur not only among individuals who take advise, but also among those who are not reached by guidance systems or do not comply. Behavioural responses, in any case, influence trip times and should be anticipated.

1.2 Objectives and contributions

The purpose of this collaborative effort is to enhance and expand the existing social routing model, particularly focusing on modifying the distribution of passenger demand. The goal is to guide travellers towards socially desired routes, effectively achieving network load balancing for a single mode of transport on various spatiotemporal scales. The approach aims to benefit from multi-modal integration, dynamically allocating public transport vehicles to alleviate congestion in specific network areas. The strategy involves refining social routing algorithms to balance societal and individual user needs by rerouting a fraction of the demand and fleet to take user-acceptable detours for overall system benefit. The project also emphasizes providing personalized pre-trip route advice through dynamic scales, considering user-induced constraints and objectives through multi-objective optimization. Additionally, the initiative includes upgrading solutions based on smart algorithms, employing machine learning to enhance fleet occupancy, automation, and optimization potential for passenger transport across both road and air. Fleet optimization techniques for operators will be developed to facilitate network load balancing, considering dynamic and stochastic network travel times. System-optimized routing techniques for fleet vehicles will be explored based on the service's penetration within the overall traffic system. Lastly, AI algorithms will be developed to optimize the scheduling and travel routes of Connected and Autonomous Vehicles connected to a hierarchical traffic management system, aiming to maximize or For the above objectives to be met in this task, we have first conducted a detailed state-of-the-art review regarding the impact of signal vehicle couple control for load balancing, social routing, prediction models for demand responsive transport and optimization techniques for urban logistics. The progress of the tasks performed during the last months have been summarized in this deliverable.

1.3 Outline of the deliverable

Section 2 provides a state-of-the art literature review about four identified problem domains namely, traffic management using signal vehicle couple control, social routing, prediction models for demand-responsive transport, and optimization techniques for urban logistics which all are related to network load balancing. Section 3 provides detailed updates on the work performed to date for the above-mentioned problems related to network load balancing and dynamic optimization. Section 4 concludes the document by providing thoughtful insights regarding the work performed and future directions.

2 BACKGROUND AND REVIEW OF EXISTING SOLUTIONS IN NETWORK LOAD BALANCING AND DYNAMIC OPTIMIZATION

This section is dedicated to the state-of-the-art literature review on traffic management with signal vehicle couple control, social routing, prediction models for demand-responsive transport and optimization techniques for urban logistics.

2.1 Traffic management: signal vehicle couple control

In Madrid, the Use Case (UC) will centre on the management of events/incidents for transport network functionalities to be restored. This will consider linked and driverless vehicles, which are not yet widely implemented in cities. As a result, the suggested Use Case will be tested using transport simulators (such as Aimsun), and two simulations will be created: one for mixed traffic (CAVs and conventional cars) and one for totally autonomous scenarios (high CAV penetration). The cars in the simulated environment will be equipped with an on-board unit or smart gadget that will allow them to communicate with their surroundings. There will be two categories of events considered: scheduled events (such as roadworks) and unexpected events (such as accidents). Our system will provide the critical functionalities from the Use Case, such as evacuation routes - lane indication, prioritization of emergency vehicles, tunnel evacuation management compliance with tunnel management regulations, control of access on the ring highway, lane management, alternative routes for avoiding specific road stretches in the M-30, and routes using alternative modes of transportation instead of road transport and private vehicles.

Given that one of the primary goals of CONDUCTOR is to develop new tools for traffic management in future mobility scenarios, CAVs could be a valuable asset in achieving this goal in the next decades. One of the most significant advances for coordinated traffic management that CAVs will bring is Signal Vehicle Coupled Control, which aims to improve traffic control performance by leveraging real-time information exchange between signals and vehicles, as well as the simultaneous optimization of signal timing/phases and CAV trajectories and/or routes, to improve the overall traffic network performance.

In isolated signalized crossings, a model for coupled control of connected autonomous vehicles (CAVs) and traffic lights is proposed in this research study (Wang et al., 2023) The model estimates the time it will take for CAVs to arrive at stop lines by utilizing real-time data on their position and speed. Phase saturation is maximized by optimizing traffic signal timing based on arrival time. Furthermore, CAVs are designed with a speed profile that maximizes speed when they approach the stop line. The technique is tested in the paper using NetLogo, a multiagent microscopic simulator, and analysis and verification are carried out at a Weihai intersection. The results of the simulation show that the proposed model performs much better than models that merely optimize the speed profile of CAVs and fixed traffic signal timing. The suggested methodology cuts the average number of stops by 47.0% and the waiting time by 41.3% when compared to these methods. With a performance gain of roughly 10% over peak hours, the optimization performs best during off-peak hours. In addition to stressing the significance of considering both traffic signal timing and the speed profile of CAVs for improved performance, the article highlights the potential of linked control in enhancing traffic efficiency and signal use at intersections. The suggested approach works well to ease traffic and enhance intersections' general operational effectiveness.

In this paper (Debarshi et al., 2022), a novel controller for autonomous cars is presented with particular attention to lateral path-tracking and longitudinal cruise control. An Extended Minimal Resource Allocating Network (EMRAN), a neural network with an adjustable Radial Basis Function (RBF), is used by the suggested controller, known as EMRAN-aided. To deal with ambiguities and outside disruptions, this network uses an online learning algorithm and a feedback error learning mechanism. The difficulties of autonomous driving are discussed, with a focus on the necessity of simultaneous control of both lateral and longitudinal dynamics. The EMRAN-aided methodology is contrasted with conventional techniques like Stanley controllers and PID controllers. The simulation results in diverse scenarios, with varying speeds and external disturbances, indicating that the EMRAN-aided controller performs better than the others in terms of tracking performance. Because of EMRAN's special qualities, which include its resilience to uncertainty, online adaptability, and compatibility with any feedback controller, it has great promise for use in autonomous car control systems. In summary, the research highlights the advantages of using EMRAN in real-time longitudinal and lateral control of autonomous cars and summarizes the contributions made.

To improve torque output stability and hydraulic energy utilization, a unique mechatronics-electro-hydraulic power coupling electric vehicle (MEH-PCEV) is presented in this study work (Yang et al., 2023). The vehicle combines an electric motor and a hydraulic pump/motor into one unit for mutual energy transfer. A cluster analysis technique is used to categorize road test data for MEH-PCEVs with multiple energy sources, offering insights for creating rule-based energy management strategies (RB-EMS). To address torque output anomalies in RB-EMS, an inverse thinking fuzzy logic optimization energy management method (FLO-EMS) is developed, which optimizes energy flow and modifies electromagnetic torque in real-time. The findings of the simulation show that the implementation of FLO-EMS reduces electric peak torque and increases the percentage of electrical energy recovery by stabilizing the production of both electric and total torque. A significant improvement in the motor operating point's overall efficiency leads to a 24.42% reduction in the rate of energy consumption. In addition to offering a fuzzy logic optimization technique for real-time torque adjustment in MEH-PCEVs, the research advances the development of electro-hydraulic coupling systems and illustrates gains in overall performance and energy efficiency. The work is anticipated to have an impact on electro-hydraulic coupling systems' engineering applications.

The study (Louati et al., 2020) tackles the difficulties that traffic control authorities encounter in contemporary cities, with a particular emphasis on the intricacies that result from increased urbanization. Without considering early prediction and estimation of occurrences, most of the Traffic Signal Control Systems (TSCS) that are now in use in the literature primarily provide real-time control for traffic difficulties that are discovered. Furthermore, problems concerning the dispatch and arrival of emergency vehicles are rarely considered. The paper presents PANNAL, a predictive and reactive TSCS, to fill in these gaps. PANNAL is a multi-agent system that uses the Longest Queue First Maximal Weight Matching algorithm (LQF-MWM), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN) in each of its individual agents. The integration facilitates adaptive signal sequences and durations, hence prioritizing emergency vehicles' crossing. For coordination, the agents use a heterarchical design. For simulation and assessment, the most recent version of VISSIM, a traffic simulation program, is used. For benchmarking, the study uses algorithms, scenarios, KPIs, and assessment findings from current literature. These algorithms are proactive, exhibiting competitive outcomes and excellent performance in traffic management during periods of erratic traffic. The research aims to contribute to the development of advanced TSCS that not only react to current traffic issues, but also predict and estimate them in advance while addressing the needs of emergency vehicles.

This work (Dai et al., 2023) explores the optimum of traffic control systems at signalized crossings by considering vehicle trajectories, lane allocations, and signal timings simultaneously. Although current research focuses on vehicle and signal control, lane assignments are typically predetermined and set. To incorporate these elements under mixed traffic situations including both connected automatic vehicles and human-driven vehicles (HVs), the research presents a two-dimensional (spatiotemporal) control method. The work uses a piece-wise linear programming approach to improve lane configurations and signal timings using pseudo-platoons. To produce smoother vehicle trajectories, vehicle trajectory control is also implemented. Through numerical experiments, the suggested control mechanism is assessed and found to perform better than actuation control in terms of vehicle travel time in both under- and over-saturated traffic scenarios. The study recognizes that CAVs and HVs will coexist while moving toward complete CAV deployment, and it attempts to offer a workable control structure that considers HV limits and capitalizes on CAV capabilities. The study highlights the necessity for combined optimization of traffic signals and vehicle trajectories (Signal-Vehicle Coupled Control, or SVCC), and examines relevant works in CAV-based traffic signal control and vehicle trajectory planning. This research tackles the mixed-autonomy traffic conditions, highlighting the absence of integrated regulation of traffic signals and lane configurations, whereas prior studies concentrated on a fully CAV environment. The study also looks at the idea of lane-based signal control and entrance lane settings, noting that dynamically modifying signal timings could not work well if traffic demands aren't considered. The entry-lane control problem includes a discussion of the dynamic lane assignment problem. The study suggests a cooperative control system called Total-Factor Control (TFC), to combine vehicle trajectories, lane configurations, and signal timings into a single system. The researched topic, the collaborative control framework, and an overview of the sections that create the collaborative control framework, explain the dynamic control process, carry out numerical experiments, and discuss the findings are presented at the end of the study.

The article (Du et al., 2021) addresses the critical role signalized junctions play in addressing urban car fuel economy and transportation efficiency challenges. With the introduction of connected and automated cars, traffic has become more varied, with different cars possessing different degrees of intelligence. The study suggests a Coupled Vehicle-Signal Control (CVSC) technique as a reaction to these modifications. To increase traffic efficiency and save energy, this technique simultaneously optimizes CAV driving trajectories and traffic signal timing. Traditionally, traffic signal control and vehicle trajectory optimization have been approached as separate issues in the optimization of signalized junctions. Nevertheless, to achieve cooperative signal-vehicle control, the suggested CVSC approach incorporates these elements. While CAV routes are optimized to minimize fuel consumption at the micro level, traffic signals are tuned to decrease vehicle delay at the macro level.

The study considers mixed traffic environments, in which CAVs and Human-driven vehicles (HDVs) coexist. This mixed traffic is analyzed using the suggested CVSC approach, which considers variables like velocity and saturation volume depending on the local CAV penetration rate. The approach demonstrates notable performance gains when compared to the conventional CACC control and the classic eco-driving model (GlidePath). Using car-following models like the Intelligent Driver Model (IDM), Cooperative Adaptive Cruise Control (CACC), and Adaptive Cruise Control (ACC), the basic graphical model of mixed traffic flow is constructed. The CVSC technique, which maximizes CAV trajectories and signal timeliness, is based on this concept. The efficacy of the CVSC approach is confirmed by simulation trials, which show 6%–14% fuel savings and 1%–5% average speed increases when the CAV penetration rate surpasses 40%. By addressing the cooperative functioning of cars and signal controllers in a mixed traffic situation and taking real-time information for optimization, the study contributes to the field. In light of the random mixing of Human driven vehicle (HDVs) and CAVs, the suggested CVSC approach, in summary, offers the potential for improving the operation of signalized junctions in mixed traffic conditions. The approach could be expanded in the future to handle multi-intersection signal coordination and consider various driving philosophies of human drivers. This research (Ghoul & Sayed, 2021) investigates the possibility of using data from Connected Vehicles (CVs) to optimize traffic networks' safety in real-time. The study focuses on intersections and presents a Signal-Vehicle Coupled Control (SVCC) system that enhances safety by combining dynamic speed advisories and adaptive traffic signal control (ATSC). Using a Soft-Actor Critic Reinforcement Learning (SAC RL) framework in conjunction with a rule-based methodology, the SVCC system distributes speed advisories to vehicle platoons upon approach and modifies signal timing accordingly. To assess the current conflict rate at the intersection and provide input for the model and performance evaluation, real-time traffic parameters are collected. Using VISSIM simulation, the suggested system is evaluated at two intersections, showing a significant reduction in traffic conflicts of 41–55% and a decrease in vehicle delays of 21–24%. With diminishing returns beyond 50%, the study emphasizes the system's usefulness at lower market penetration rates. It is argued that this Signal-Vehicle Coupled Control architecture offers a computationally effective way to optimize safety in real-time at signalized junctions. The introduction highlights the frequency of rear-end incidents at junctions with traffic signals and highlights the contribution of CVs to increased safety. To provide the groundwork for the proposed Signal-Vehicle Coupled Control system, the study examines current intelligent transportation systems, including Green Light Optimal Speed Advisory (GLOSA), Adaptive Traffic Signal Controllers (ATSCs), and Vehicle-to-Infrastructure (V2I) communication. The methodology section describes how the hybrid dynamic programming-reinforcement learning strategy was used to construct the SVCC framework. To estimate conflict rates, safety performance functions based on shockwave characteristics are used. Considering both temporal and spatial characteristics, the environment state representation leverages aggregated data to overcome the difficulty of representing individual cars inside the Dedicated Short-Range Communication (DSRC) range. PTV VISSIM simulation software is used in the validation and testing segment to model junctions based on actual data. Vehicle behaviour is represented by the Wiedemann 99 car following model, and detector loop systems and signal timing schemes are utilized to calibrate test junctions. The data from connected vehicles is used to inform the Reinforcement Learning algorithm's decisions on speed advisories and signal time extensions. Connected vehicles are modelled independently. The new approach of the SVCC system in optimizing safety through real-time modifications to vehicle trajectories and signal timing is highlighted in the conclusion. The study highlights the need to consider all possible approaches at the intersection and reports notable improvements in safety and delays. Notwithstanding its efficacy, the report notes many drawbacks, including the requirement for case-specific research, the possible influence of inaccurate data, and difficulties in guaranteeing adherence to speed advisories. Suggestions for further study include field testing to evaluate theoretical benefits in real-world circumstances, including more data from connected vehicles, and investigating additional safety measures. The importance of more research and field testing is emphasized in the paper's conclusion to validate the suggested Connected Vehicle-based Signal-Vehicle Coupled Control system. The authors of this study (Q. Guo & Ban, 2023) present a comprehensive and novel multi-scale modelling and control system designed to tackle the complex problems of urban traffic control, especially in relation to connected and automated vehicles . To improve the overall quality and efficiency of transportation systems, a comprehensive strategy is required due to the complexity of urban traffic control, which is characterized by several temporal and spatial scales. The writers concentrate especially on the two-scale SVCC issue in a setting where CAV penetration is complete. By utilizing a Model Predictive Control (MPC) scheme, the suggested framework introduces a stability analysis technique based on the idea of key state consistency between the two scales. The goal of this strategy is to offer a strong answer for the SVCC issue when CAVs are present. The authors provide numerical findings and thorough comparisons with benchmark approaches to demonstrate the framework's efficacy and highlight its potential benefits. The multi-scale modelling framework's introduction, its application to the SVCC problem in the presence of CAVs, and the paper's incisive comments on possible extensions to handle mixed traffic flow and tri/multi-scale urban traffic control scenarios are among its main contributions. The authors emphasize the significance of stability analysis, especially in situations involving Human-Driven Vehicles (HDVs), and they push for the investigation of coordinating techniques for corridor management in their discussion of future research topics. The research also highlights the need to design stability analysis techniques specific to tri/multi-scale control settings. The authors emphasize the importance of continued study to guarantee the stability and suitability of the suggested multi-scale framework for Urban Traffic Control (UTC) in the context of unmanned aerial vehicles (UAVs). Therefore, this study makes a fundamental contribution to the rapidly developing subject of intelligent transportation systems by presenting a methodical and progressive strategy for addressing the difficulties associated with managing urban traffic in the era of automated and networked cars.

Exploring the nexus of CAVs and traffic signal optimization, various studies delve into innovative models and controllers. Researchers propose a coupled control model that leverages real-time data for CAVs, optimizing traffic signal timing to improve efficiency in isolated signalized crossings. However, there is a general call for extending these models to encompass more complex urban traffic scenarios. In a distinct approach, an Extended Minimal Resource Allocating Network -aided controller showcases superior performance in lateral and longitudinal control for autonomous vehicles. The broader applicability and potential limitations of such controllers remain key focal points for future research. Additionally, the integration of mechatronics-electro-hydraulic power coupling in electric vehicles demonstrates promising outcomes in torque stability and energy efficiency through fuzzy logic optimization. While simulation results are encouraging, practical field testing and comprehensive evaluations are deemed essential for the broader implementation of these technologies. Collectively, these studies underscore the continuous advancements in CAV- and electric vehicle technologies, emphasizing the ongoing need for research to address specific gaps and challenges in real-world applications. The studies collectively underscore challenges in current traffic control systems, emphasizing the need for advancements in urban traffic management. Existing Traffic Signal Control Systems (TSCS) often lack early prediction and estimation capabilities, primarily offering real-time solutions for identified traffic issues. Emergency vehicle dispatch and arrival pose additional challenges, often overlooked in current systems. To address these gaps, research introduces innovative models like PANNAL, a predictive and reactive TSCS utilizing multi-agent systems and advanced algorithms. In parallel, optimizing traffic control systems at signalized crossings necessitates a holistic approach considering vehicle trajectories, lane allocations, and signal timings concurrently, especially in mixed-traffic environments. The coexistence of connected autonomous vehicles (CAVs) and human-driven vehicles (HVs) requires a comprehensive Signal-Vehicle Coupled Control (SVCC) strategy for improved traffic efficiency. Additionally, in addressing urban transportation challenges, the proposed Coupled Vehicle-Signal Control (CVSC) technique optimizes CAV driving trajectories and traffic signal timing simultaneously, exhibiting notable gains in fuel savings and average speed increases in mixed traffic conditions. These research endeavours collectively highlight the broader need for integrated, predictive, and adaptive traffic management solutions to address contemporary urbanization challenges comprehensively.

2.2 Social routing

The growth in urban population is likely to result in increasing pressure on the mobility system. Currently, road capacity and public transport supply are oftentimes insufficient to facilitate current demand, let alone a further increase. The high and expected increase in congestion levels affect not only accessibility and economic efficiency but is also the source of many negative externalities such as noise and GHG emissions, impacting the quality of life and social progress (Stiglitz et al., 2009). The need for interventions in transport comes from the fact that individuals are typically selfish, i.e., concerned with their own utility, when making decisions (Ben-Akiva & Lerman, 1985; Eikenbroek et al., 2023). Adopting a game-theoretic modelling perspective, it can be assumed that in the long run the travel demand distribution over the different subsystems and networks is close to an equilibrium

(Klein, Levy & Ben-Elia 2018), in which – according to the definition of Nash (1950) - travellers cannot improve utility by unilaterally changing mode, departure time or route. Theoretical examples (Braess, 1968; Roughgarden, 2005) that consider route choice in road traffic networks illustrate that such selfish behaviour may lead to suboptimal performance compared to the *system optimum*. More recent studies in public transit (Luan & Corman, 2022) and real-world examples (ref Colak et al. (2016); Van Essen et al., 2020) confirm this observation. The system optimum, however, is considered to be a purely theoretical state, used as a reference to compare with other demand distributions, e.g., using the efficiency loss as expressed by the Price of Anarchy (Roughgarden, 2005). The system optimum suffers from unfairness or equity issues in the sense that the realization of it may require a portion of the travellers to make sacrifices for the benefit of others (Jahn et al., 2005; Klein et al., 2018; Van Essen et al., 2020), both in comparison with the baseline equilibrium as well as in comparison with other travellers. These within- and between-state differences complicate attaining or maintaining the system optimum over time (van Essen et al, 2020), and authority-traveller interaction is therefore often modelled as a win-loss game (Vreeswijk, 2015), and a fairness-efficiency trade-off (Eikenbroek et al., 2022, Morandi 2023).

Empirical studies however indicate that travellers do not always make rational decisions – at least from an outside perspective (e.g., Ciscal-Terry et al, 2016; Djavadian et al., 2014; Zhu & Levinson, 2015), e.g., due to the lack of information and or their cognitive capabilities in decision-making processes, also known as `bounded rationality' (Mahmassani & Chang, 1987; Simon, 1997). Research in traffic psychology shows that assessing the quality of travel alternatives could be difficult for some travellers, or they are not willing to switch to an alternative option if the benefit of switching is not significant (Vreeswijk et al., 2015). In our context, authorities can exploit this partly rational behaviour during decision-making in the sense that system performance can be improved by degrading the level of service for a group of users without them caring or knowing, or at least not inducing a change in travel behaviour. In the game-theoretical setting, this leads to a boundedly rational user equilibrium (Eikenbroek et al., 2018), with users making individually sub-optimal yet acceptable choices for themselves. Considering this concept of bounded rationality in the context of transport interventions means that some of the sacrifices as aforementioned become possible, i.e., the network can be steered towards a state closer to the system optimum while respecting individual tolerances. Evidently, a significant degradation in the level of service (LoS) *will* be noticed and induce a change – at least in the long run - indicating that authorities should adopt a dual-notion approach (utilitarianism and sufficientarianism), i.e., everyone should be provided with a minimum LoS when maximizing contributions to social welfare (Gonzalez et al., 2022).

The threshold of an attribute change below which individuals do not re-consider their travel choices is referred to as the *indifference band* (Mahmassani and Chang, 1987, Vreeswijk, 2015). This attribute change can either occur in reference to an alternative, e.g., road users will not re-consider their route since their gain by a unilateral change is less than this threshold (Di et al. 2017), or in reference to a habitual choice, e.g., the degradation (or improvement) in LoS when making the usual travel choices (Vreeswijk et al., 2013). Theoretically this suggests that if through intervention the LoS changes compared to a baseline situation while the indifference bands are respected, no potential behavioural responses are invoked. Scholars have particularly adopted this notion in route choice studies, assuming that a sub-optimal route advice is perceived to be acceptable as long as it is only slightly worse than the best one (Eikenbroek et al., 2022; Di et al. 2016) and the habitual choice (Jahn et al. 2022). It has been indicated (Eikenbroek et al. 2018; Morandi 2023) that the indifference band could be calibrated based on real-world data, and several previous scholars have studied this concept (e.g., Vreeswijk et al. 2015; Di et al. 2017). These studies, however, focus on a single attribute (e.g., travel time), or a single user group (e.g., car drivers), although practice is much more complex with various attributes playing a role when making travel decisions and many user groups interacting, particularly in an urban setting.

2.2.1 Literature review

In the remainder of this chapter, we provide an overview of literature discussing the estimation and or use of indifference bands in the context of traffic and transport management. For the most relevant literature to be selected, different search engines, including Scopus, Google Scholar, and Research Rabbit are used. Different combinations of the keywords (e.g., travel time, waiting time, delay, and indifference bands) are used in the aforementioned search engines. In Scopus advance query, for instance, we combined multiple keywords such as travel time, delay, waiting time, and indifference bands. Since the concept of indifference bands is used in many fields, the subject area is limited to ‘engineering’, ‘social science’, ‘computer science’, and ‘mathematics’, where 18 results were found. The following search query was used to find relevant studies.

((TITLE-ABS-KEY(travel AND time)OR TITLE-ABS-KEY(waiting AND time)OR TITLE-ABS-KEY(delay))AND TITLE-ABS-KEY(indifference AND band*)) AND (LIMIT-TO(SUBJAREA ,"ENGI")OR LIMIT-TO(SUBJAREA , "SOCI")OR LIMIT-TO(SUBJAREA , "COMP")OR LIMIT-TO(SUBJAREA , "MATH"))*

The systematic study selection process consists of three rounds. In the first round, any relevant literature found by the search engines is included. After screening the abstracts, non-relevant studies are excluded. In the second round, we used snowballing to find similar studies that were not found by the search engine through the above query. The final list of studies is presented in Table 1 for our literature review.

Mahmassani and colleagues started incorporating the concept of bounded rationality from Herbert Simon into travel behaviour in the late 1990s, known as ‘indifference bands (IBs)’. The concept of IBs implies that travellers often do not change their behaviour if changes in their travel attributes are below certain thresholds, or in other words, perceptually the utilities do not change. Since the relative importance of different travel attributes varies among individuals, the minimum acceptable thresholds vary accordingly (Vreeswijk et al., 2013). Generally, when the attribute changes exceed certain thresholds, travellers are prone to adjust their travel behaviour. For instance, (Carrion & Levinson, 2019) studied the day-to-day choice of 65 commuters for 30 days and found that commuters switch to alternative routes if the travel time of their main routes increases beyond a threshold.

Table 1 Overview of literature selected

Category	Approach	Parameters	Attributes	Study
Simulation	Methodological	Travel time, real-time information, signal control	Route choice, departure time, en-route choice	(Hu & Mahmassani, 1997)
Interactive travel simulator	Methodological	Real-time traffic information, schedule delay	Route choice, departure time	(Liu & Mahmassani, 1998)
Interactive travel simulator	Behavioural modelling	Real-time information reliability, users’ characteristics	Departure time, route switch	(Mahmassani & Liu, 1999)
Stated preference survey	Behavioural modelling	Real-time travel information, travel time, travel cost	Freeway route switching	(Jou et al., 2005)

Category	Approach	Parameters	Attributes	Study
Video survey	Behavioural modelling	Actual waiting time, red wave, number of stops, intersection characteristics	Perceived waiting time	(van der Bijl et al., 2011)
Theoretical framework	Behavioural modelling	Travel time, changes in the network	Effective control space, route switch	(Vreeswijk et al., 2013)
Survey	Behavioural modelling	Travel cost	Route and departure time choice	(Han et al., 2015)
Simulation	Behavioural modelling	Travel time, queue length, perception error	Route switch	(Vreeswijk et al., 2015)
Literature review	Models and methodologies	Substantive and procedural bounded rationality models	Two-stage cognitive, day-to-day learning	(Di & Liu, 2016)
Simulation	Methodological	Travel time	Boundedly rational user equilibrium, route choice	(Sun et al., 2016)
Survey	Behavioural modelling	Travel time, perceived safety	Route switch	(Di et al., 2017)
Simulation	Methodological	Travel time	Route choice	(Eikenbroek et al., 2018)
Simulation	Methodological	Fixed vs. flexible transit routes, vehicle size, service zone, total cost	Modal shifts, smart transit	(Guo et al., 2018)
Simulation	Methodological	Value of travel time reliability and adaptive expectation formation	Learning rate and indifference bands	(Fu & Zhang, 2020)
Simulation	Methodological	Incomplete and imperfect information	Route and departure time choice	(Yu et al., 2020)
Survey	Behavioural modelling	Absolute and relative travel time saving	Route choice	(González Ramírez et al., 2021)

However, the margin of such thresholds is fuzzy and therefore impossible to draw a concrete conclusion that route switches occur due to changes in a single attribute. This was revealed in the route choice experiments conducted by Hu and Mahmassani (1997), Liu and Mahmassani (1998) and Mahmassani and Liu (1999). That is, travellers do not switch to shorter paths due to the existence of inner inertia even though information about the path costs was available to them. Such inertia may stem from past experiences or habitual choices. Certain learning principles play a role in the adaptation of travel choices, and therefore commuters usually do not update their perceptions if they are unaware of the changes (Vreeswijk et al., 2013) or the changes are within their IBs (Di & Liu, 2016). Vreeswijk et al. (2013) divided drivers' route choice behaviours into three categories which could also be applied in route switching: (1) logical behaviour where drivers switch to better alternatives, (2) cognitive behaviour where drivers do not actively look for better alternatives if they are satisfied with their current route to reduce mental workload and (3) irrational behaviour where drivers choose the worst alternative.

Travel time and cost are commonly used attributes to evaluate travel behaviour, such as trip planning, transport modes, and routes (Vreeswijk, 2015). In bounded rationality user equilibrium (BRUE), the flow-dependent travel time is assumed to be the only factor determining route choice (Di & Liu, 2016). Vreeswijk et al. (2015) studied various IBs to improve network performance on freeways. The authors found 600 seconds to be the maximum IB between travel times in the main route and the alternative one, below which the main route is still the preferred choice. Furthermore, studies show that long waiting time at signalized intersections is another decisive factor in route choice. Even though the total travel time could remain below the threshold as presented in Vreeswijk et al. (2015), if perceived or actual waiting time exceeds a threshold, anxiety and stress start to build up, which could potentially result in route switches. According to Van der Bijl et al. (2011), the upper and lower IBs for perceived waiting time are 42 and 90 seconds, respectively. The waiting time below 42 seconds is generally accepted and above 90 seconds could result in red-light crossing or route switch. This is of high importance to know when travellers are more susceptible to travel information and route-switch and, hence, advise social routing or set conditions for signal priority for heavy-duty vehicles. However, studies show that many other factors play roles in forming and adapting route choice, as well as route switches. Studies show that drivers do not only explore routes with less travel time but also routes that require cognitive processes (Di & Liu, 2016). Moreover, it is worth mentioning that travel decisions are also context-dependent and alternatives are chosen in terms of gain and loss relative to some reference points (Vreeswijk et al., 2015). This refers to prospect theory in which losses weigh twice the gains of equivalent size. Based on this theory, drivers are more likely to notice changes in their travel attributes that involve losses than gains. Furthermore, some secondary factors such as the number of stops, average travel speed, landscape, and presence of trees also influence drivers' route selection (Flannery et al., 2005).

Furthermore, travel choices are also subject to uncertainties in transportation systems, which makes people even more boundedly rational (Sun et al., 2016). Travellers do not exactly know the variability in their travel times or are unaware of the alternative routes. For instance, a study in Minnesota, United States, found that nearly 33% of the chosen routes by normal travellers were slightly longer than the shortest routes, which decreased to 11.3% for commuters (Zhu & Levinson, 2015). Therefore, real-time information becomes of high importance in reducing uncertainties in their route choice, as well as route switch. Jou et al. (2005) explored various types of real-time information, namely qualitative, quantitative, qualitative with guidance and quantitative with guidance, to model route-switching behaviour on freeways in Taiwan. The authors concluded that travellers on freeways are inclined to switch routes when quantitative (travel time and cost) and guidance information are provided on Variable Message Signs (VMS). However, even though the study demonstrates that travellers tend to switch routes when providing them with traffic information, the study does not provide any results when travellers decide to switch their routes apart from the fact that young and high-income travellers are more likely to change to the best routes. In addition, the study does not explain the (relative) magnitude of travel time and cost savings that trigger route-switch.

Overall, boundedly rational travel choices of individuals should be considered and anticipated when designing and evaluating measures to improve network performance. Consequently, informed decision-making asks for incorporating the concept of IBs in traffic models, due to the collective responses of travellers to any traffic management measure, influencing its performance in practice. In this regard, IBs provide better insights into when and where changes in travel attributes trigger travel behaviour changes, primarily route switches. Based on this premise, optimal traffic management policies (e.g., signal priority and social routing) can be adapted to obtain the best possible outcome. However, defining the margins of IBs is a challenging task. Generally, we can argue a larger size of IBs means that travellers are reluctant to switch choices and vice versa (Yu et al., 2020).

Within the CONDUCTOR project, we consider two possible applications to improve network performance without major supply adaptations by exploiting the indifference band of travellers. Section 3.2 presents a framework to improve local traffic conditions for specific user groups (trucks) through prioritization while the LoS of other users are such that the change in travel utilities is within the indifference band, and, hence, no substantial travel behaviour changes are provoked or safety hazard is induced (e.g., red-light crossing). This setting is also considered in real life in the context of Use Case 1 - Almelo. In addition, Section 3.2 presents a methodological framework for social rerouting, a travel demand management measure where a portion of travellers is rerouted onto sub-optimal yet acceptable paths in the interest of network-wide travel conditions.

2.3 Prediction models for Demand Responsive Transport

Within the Slovenia use case, we will address the challenge of poor public transport connections between Slovenian cities and airport(s) in neighbouring countries. Cross-border transport is growing because there is a limited offering of flights from Slovenian airports (or they are too costly). As a result, passengers often prefer airports in neighbouring countries for their departing destination. There is an increasing need for a flexible public transport system for intercity/interregional trips, which may enable people to commute short distances in affordable, reliable and sustainable ways. To allow efficient cross-border traffic integration, the traffic operators must have the observability of traffic demand (and predictions) and the capability to operate and react to traffic events (such as changes in service demand) in real-time. The dynamics of traffic services mediate the services' availability and quality, reflected in final cost-effectiveness.

Prediction modelling enables us to anticipate demand and fluctuations. An accurate prediction enables us a better use and management of the transport fleet of the demand-responsive transport service. In the development of a demand-responsive platform, we intend to use the benefits of demand predictions to improve operational efficiency and reduce usage wastage and idle time of the fleet.

2.3.1 Background on prediction modelling

In traffic forecasting (F. Guo et al., 2018) often the complex temporal and spatial dependencies must be considered. Temporal dependencies relate to periodic trends, such as rush hours or seasonal changes, while spatial dependencies describe how changes in traffic on one road may affect adjacent roads due to the topological structure of the road network. Successful prediction based on traffic patterns requires the inclusion of both types of dependencies along with various covariates. It has also been shown that multi-target models that capture dependencies between different targets and transfer information between them can also improve generalization (Huang et al., 2014; Jin & Sun, 2008).

Given the ever-increasing amount of data, traditional statistical approaches are sometimes insufficient to effectively model complex time-dependent interactions (Makridakis et al., 2018; Spiliotis et al., 2020). As a result, recent methodologies are increasingly turning towards more complex machine learning (ML) models. However, drawing a clear line of differentiation between statistical models and ML-based models is often vague and poorly defined (Barker, 2020).

The first approaches used classical machine learning methods where temporal dependencies were added by including lag features and treating problems as tabular problems (Kumar & Thenmozhi, 2006; Luk et al., 2000; Mei et al., 2014). Further improvements in accuracy have been achieved by incorporating more complex neural network-based models, such as RNN (Medsker & Jain, 2001), where connections between neurons can be organized in a cycle. Such models are better suited for handling temporal dependencies and have been successfully used for modelling traffic (Yun et al., 1996). Later improvements in modelling temporal data, such as the introduction of Long Short-Term Memory (LSTM) cells (Gers et al., 2002), were also quickly adopted for the field of traffic forecasting (Zhao et al., 2017). Almost in parallel with the advances in temporal modelling with LSTMs, convolutional neural networks (CNNs) (O'Shea & Nash, 2015) also became increasingly popular. Although originally developed for image classification, they were adapted for time series modelling (Bai et al., 2018) and successfully used for traffic forecasting (G. Li et al., 2021; J. Zhang et al., 2017; Zhao et al., 2017). More recently, there has been a focus on developing architectures that are more specialized for time series modelling. One of the popular approaches for univariate time series point forecasting is the N- BEATS (Oreshkin et al., 2019) architecture, which is well suited for forecasting problems where large amounts of data are available. Similarly, DeepAR (Salinas et al., 2020) is a popular forecasting neural network that uses LSTM cells to predict parameters of a probabilistic distribution and provides more information about the uncertainty of the model. It can handle multivariate time series with future and past covariates. Lately, transformer-based (Lim & Zohren, 2021) neural networks such as Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting (Lim et al., 2019), have also been used for predicting freeway traffic speed (H. Zhang et al., 2022). Although deep learning techniques are widely used for forecasting, one should not ignore other approaches that have also been successfully used for accurate traffic forecasting, e.g, XGBoost (Dong et al., 2018).

Even though advanced computing methods are becoming a standard tool for smart mobility solutions there are still several open questions that need to be addressed to bring these methods into widespread use. One important aspect of all real-world systems is the presence of rare events which are difficult to model with data-driven techniques. Current methodology handles these by incorporating expert knowledge into the prediction (Qi & Majda, 2020), however, if the general dynamics of the system is not known, which is the case for socially driven systems, more elaborate methods are required (Ashraf et al., 2023). In spatio-temporal modelling especially, we have fields of study related to probabilistic modelling (Wen et al., 2023), explainability and robustness (Pham et al., 2023), and representation learning (Xie et al., 2023) that are less mature compared to other machine learning varieties such as image analysis or natural language processing. This is in most part due to the special properties that time series data possesses, most notably arbitrary long-term dependencies in the input sequences and causality. However, the literature on this topic is rapidly expanding with an increasing number of use-case-specific techniques which circumvent these problems which pave the road toward robust solutions in data-driven prediction modelling.

2.4 Optimisation techniques for urban logistics

The integration of urban distribution of goods in the supply infrastructure for DRT service will be the foundation of the urban logistic Use Case (UC3), which will research and provide solutions for last-mile delivery.

Information on the need for goods delivery will be used to determine whether oversized PT routes can safely and effectively meet the demand for products, as well as to build goods delivery services based on DRT underused periods. The effects of reduced traffic on the overall transportation system (such as average travel times, total vehicle miles travelled, total vehicle travel time, total vehicle emissions, etc.) due to the transfer of goods delivery trips to underutilized DRT and public transportation will be evaluated considering different demand-supply balancing strategies aiming at optimisation of the performance of the overall transport network.

This section establishes a state-of-the-art analysis in the context of CONDUCTOR dynamic planning and optimization necessities, including last-mile vehicle routing, assessing suitable technologies, methodologies and approaches to highlight improvements for network management and urban planning. It does so by providing exact mathematical models complemented with a class of approximation algorithms establishing the trade-off between time and prevision.

From a mathematical perspective, different models for vehicle routing problems (VRP) and optimization are assessed along with their problem domain. These include the Rich VRP, Stochastic VRP, Dynamic VRP and Multi-Objective VRP along with their individual advantages and examples. In parallel, a multitude of optimisation method proposals (Elshaer & Awad, 2020) have also emerged, ranging from exact to approximate and hybrid methods. Having said that, the objective of this section is to review the state-of-the-art in terms of the VRP optimisation models and optimization methods most aligned with CONDUCTOR's objectives, as well as to assess their main strengths and weaknesses.

With this objective in mind, the rest of this section is structured as follows. Section 2.4.1 reviews the state-of-the-art VRP variants that are most aligned with CONDUCTOR's objectives and in particular with Task 3.4. Section 2.4.2 shows the state-of-the-art regarding the most commonly used optimisation methods to solve these VRP variants.

2.4.1 Mathematical Models for Vehicle Routing

Among routing problems, the Travelling Salesman Problem (TSP) (Gass & Fu, 2013) stands out as one of the challenges, alongside the VRP and the Problem of Allocation of Routes to Vehicles (Golden et al., 2008). The TSP has been extensively studied and is considered a fundamental problem in computer science. In the TSP, a group of customers and a vehicle are involved, with the primary objective being to determine an optimal route that begins and ends at the same point, visiting each node exactly once to minimise the overall trip cost (Mor & Speranza, 2020).

Within the context of the VRP, the primary aim is to identify the most efficient set of routes with the minimum possible cost. This involves ensuring that each route starts and ends at the designated depot, every client is visited only once, and the cumulative demand of clients visited on a route does not exceed the vehicle's capacity. These problems fall within the realm of combinatorial optimization and are categorised as NP-hard, indicating that obtaining an optimal solution becomes computationally challenging as the graph size increases (Adewumi & Adeleke, 2018).

The VRP is conventionally represented on a graph, where V denotes the set of vertices, A is the arc set, and C is a cost matrix defined over V, signifying distances, travel times, or travel costs. The objective of the VRP is to determine a set of routes for identical vehicles stationed at the depot, ensuring that each vertex is visited exactly once while minimising the overall routing cost. In the classical VRP version, components include a group of customers, a fleet of vehicles with limited capacities, and a central warehouse (Braekers et al., 2016).

Real-world scenarios often introduce uncertainty into the VRP. This uncertainty may take various forms, such as varying demand, unpredictable travel times, and unexpected events like vehicle breakdowns. The Stochastic Vehicle Routing Problem (SVRP) is a VRP variant where one or more parameters are stochastic, represented by random variables with known probability distributions (Berhan et al., 2014). Beyond uncertainty, dynamic elements characterise real-world applications. In the Dynamic VRP (DVRP), also known as real-time or online VRP, certain input data is disclosed or modified during the distribution planning dispatching phase. Primary dynamic events in VRPs involve the real-time arrival of new customer pick-up/delivery requests or variations in service and travel times (Pillac et al., 2013).

Dynamic vehicle routing problems (DVRP) introduce additional complexities, with decisions affected by new elements and increased degrees of freedom. Real-time arrival of customer requests during operations is a common source of dynamism in vehicle routing. Additionally, travel time serves as a dynamic component in most real-world applications (Psaraftis et al., 2016). This category of problems has gained popularity for modelling just-in-time supply systems, leveraging technological advancements such as mobile devices or sensors, enabling dynamic adjustments to plans during route execution (Okulewicz & Mańdziuk, 2019).

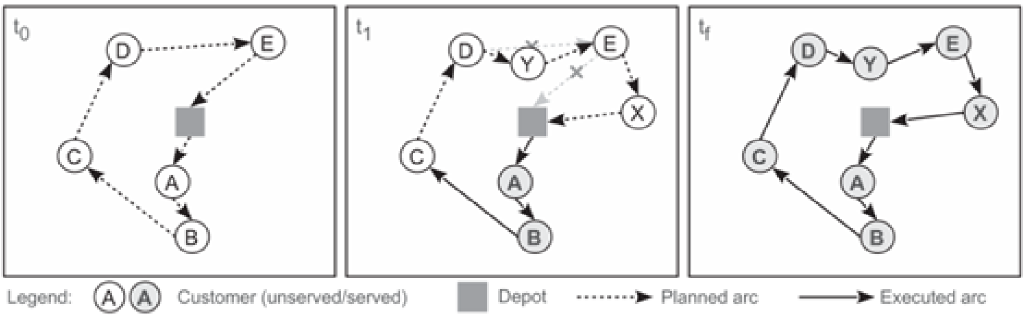

Figure 1 Example of Dynamic Vehicle Routing

In the classic DVRP, vehicles with fixed equal capacity, depart from a depot to deliver products to a number of customers at demand points. Each customer has a known demand, where n is the number of customers. It is assumed that the quantities demanded are less than the maximum capacity of the vehicles. Meanwhile, new customers with known demand emerge dynamically over time. A graphical example of the classic VRP is shown in Figure 1.

When addressing the VRP in practical scenarios, especially in last-mile environments, optimising solely for the distance travelled or working time proves insufficient. Diverse objectives or performance metrics, including cost or emissions, necessitate careful optimization. Moreover, these objectives frequently clash with one another, introducing intricacies into their collective optimization. Multi-objective VRP (Jozefowiez et al., 2008) models offer a deviation from the traditional VRP by concurrently optimising two or more objectives or performance metrics.

2.4.2 Optimization Techniques for Vehicle Routing

VRPs variants can be classified into three levels according to the degree of realism of their associated models. Aligned with this realism in the modelling, the class of optimization techniques used to solve them usually vary (Adewumi & Adeleke, 2018; Caceres-Cruz et al., 2015), as shown in Figure 2. Using this classification as a reference, we will review in the next part of this section the main categories of optimization algorithms used to solve the VRPs.

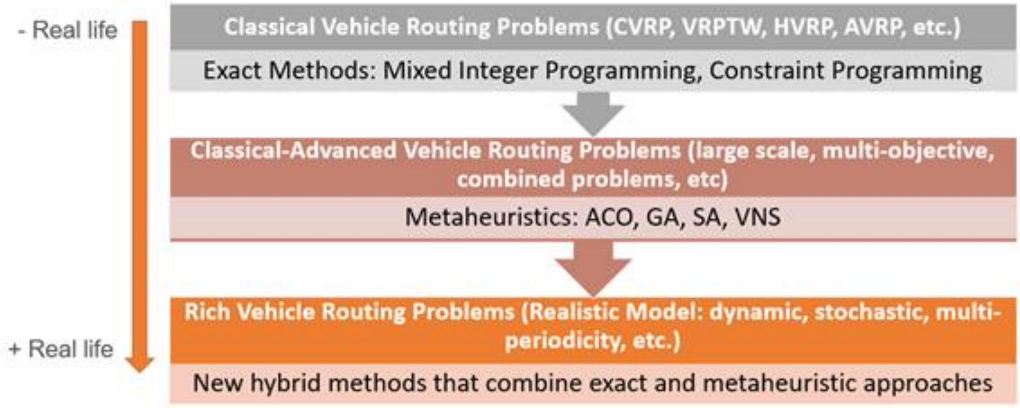

Figure 2 Model's classification and optimisation techniques

Since the classical VRP problem is NP-hard in the strong sense, all sub-variants are also NP. This means that there is no deterministic algorithm that guarantees the finding of the optimal solution within a computation time that is bounded by a polynomial in the input size. This means that only small-size instances can be handled by exact methods(Baldacci et al., 2012).

Metaheuristics are widely recognized as efficient approaches for many hard optimization problems(Potvin & Gendreau, 2019). They represent a core research field in combinatorial optimization, the VRP is an NP-hard problem and furthermore, its real-life VRP applications are considerably larger in scale. Therefore, metaheuristics are often the more suitable solution approach for practical applications. One of the main metaheuristics in the referenced literature used to solve the VRPs is the Large Neighbourhood Search (LNS), a meta-heuristic in which the neighbourhood of a solution is defined implicitly by destroying and repair operators. A destroying operator ruins a part of the current solution while a repair operator rebuilds the destroyed solution. Typically, the destroy method contains some randomness such that different parts of the current solution are modified so that enabling exploration of the solution search space. This exploration technique enables larger neighbourhoods to be visited in comparison to standard neighbourhoods of classical local search methods. This property has made this method the state-of-the-art in many variants of the vehicle routing problem(Ghilas et al., 2016; Grangier et al., 2016) and is also the reason why it is the method most commonly implemented in many software libraries and packages related to this field (Abdirad et al., 2022).

In recent years, for the resolution of VRP problems, hybrid algorithms have emerged as a powerful tool to solve them, especially for the most complex VRP variants. Hybridization has become a very promising strategy for designing better metaheuristics methods, because of their greater flexibility, less strict mathematical formulations, and higher robustness. In this way, they provide a very suitable tool to develop solvers for VRP, and as a matter of fact, they have become state-of-the-art in many variants of the rich VRP (Goel & Bansal, 2019). Following the well-known taxonomy of hybrid algorithms proposed in (Raidl, 2006), we will review significant literature in this area by considering three classes of hybrid algorithms: metaheuristics hybridized with metaheuristics, metaheuristics hybridized with problem-specific metaheuristics, and metaheuristics hybridized with other Operational Research (OR) or Artificial Intelligence (AI) techniques.

2.4.3 Optimization for Demand Responsive Transport and Logistics

The previous section presented the optimization methods used for general VRPs. This section deals with the state-of-the-art methods available for a combination of DRT and logistics.

The DRT, more specifically ride-hailing services, falls under the category of stochastic and dynamic VRP (SDVRP) — the customer requests are dynamically added to the system and assigned to vehicles. To reduce the empty vehicle kilometres travelled, the literature generally uses shared rides or ride-pooling (Engelhardt et al., 2019; Ruch et al., 2021). However, this also significantly increases the problem complexity due to a higher number of possible combinations between vehicle and customer locations. Most state-of-the-art methods, therefore, heavily utilize explicit time constraints on customer pickups and in-vehicle travel times to reduce the complexity and computation time (Alonso-Mora et al., 2017; Ma et al., 2015; Santi et al., 2014). In contrast to DRT customers, the freight requests are often less time critical. This makes a pure customer-oriented DRT method computationally intractable when combined with freight requests. The following briefly discusses the methods found in the literature for a combined DRT system with passengers and same-day freight delivery.

Even though ample literature is available on the problem of passengers and goods transport in dedicated networks, the question of combined service with shared transport resources is far less researched in the literature (Mourad et al., 2019). However, with the increasing focus on shared mobility systems, the research is gaining momentum. For example, (B. Li et al., 2014) studied a share-a-ride problem for passengers and parcels using taxis. Additionally, they proposed a less complex freight insertion problem (FIP) whereby the freight request is inserted into an already-built vehicle path for passengers such that the service quality of passengers is not significantly reduced. Given the complexity of the overall problem, the formulation did not allow the pooling of multiple passengers, and later, they also introduced an adaptive LNS approach to solving the problem (B. Li et al., 2016). (Beirigo et al., 2018) provided another formulation where they allowed the pooling of passengers and different-sized parcels in the same trip. (Arslan et al., 2019) studied a crowd-sourced delivery system using the excess capacity on trips already taking place. In this system, the self-employed ad-hoc drivers deliver the parcels on their way home or to work. A backup fleet of vehicles is kept serving the unmatched parcels. Additionally, the method introduced assumes explicit time-windows provided by both ad-hoc drivers and parcel requests. It should be noted that while the above studies combine DRT with logistics, the solution methods often are only tested on small problem instances and network. Nevertheless, they provide important groundwork for more practical methods applicable to bigger networks. The studies on large networks and large problem instances are still quite limited. For example, Manchella et al. developed a reinforcement learning based approach using the New York City taxi dataset and network (Manchella et al., 2021). The approach used multi-hop transit mode for a joint transportation of passengers and goods. The approach showed significant improvement over transit mode without multi-hop and over separate transportation of passengers and goods. Fehn et al. used agent-based simulation in the city of Munich using real freight data to study the impact of combining DRT with freight requests (Fehn et al., 2021, 2023). They assume that the operator knows all the freight requests beforehand and only the passenger requests are dynamically added to the system. They study three heuristics for accommodating freight requests into the vehicle routes. As discussing all of the optimization methods available in the literature is beyond the scope of the current section, for a more detailed review of available methods, refer to the survey by Mourad et al. (Mourad et al., 2019)

3 NETWORK LOAD BALANCING AND DYNAMIC OPTIMIZATION TECHNOLOGIES

In a transport network, the route distribution of Connected and Autonomous Vehicles is a key component of the load-balancing optimization process. CAVs may dynamically adjust their routes in real-time based on traffic conditions by utilizing advanced sensing and communication technology. This allows them to effectively re-distribute themselves across different routes to reduce congestion and avoid bottlenecks. By avoiding possible bottlenecks, this dynamic routing optimization in conjunction with machine learning algorithms for predictive traffic management allows for a proactive approach to load balancing. Furthermore, cooperative communication between CAVs promotes cooperative traffic flow by enabling cars to plan their routes and arrange themselves to avoid traffic jams. Additionally, assisting in effective signal control, flow regulation, and congestion reduction at key intersections is the adaptive interaction with traffic signal systems. By maximizing travel routes and reducing idle time, the ecologically sensitive route allocation of CAVs not only increases overall network efficiency but also lowers emissions, and fuel consumption, and promotes a more sustainable urban mobility ecology.

3.1 Traffic management: signal vehicle couple control

This section is dedicated to the progress of the work performed related to traffic management using SVCC with CAVs for network load balancing.

3.1.1 Proposed innovation

We evaluated the following assumptions in order to answer this problem: There is a fleet of fully CAVs that are linked to Traffic Management Centers (TMCs) and can be operated by numerous TMCs (hierarchical control). We further assume that the origin and destination of each CAV are known to the corresponding TMC, and that there are one or more pre-defined pathways between each origin and destination. We investigated mixed traffic scenarios and fully autonomous scenarios in this problem. The goal is to optimize the path assignment for the whole CAV fleet (determine the percentage of CAVs that take each origin-destination (OD) pair and path) as well as the traffic control plan on specific arterials of the studied network.

3.1.2 Specifications

This section encompasses a set of specifications intended for the routing and management of connected and autonomous vehicle fleets. Fundamentally, the approach is based on a sophisticated sensitivity analysis that makes use of simulations to examine various scenarios and how they affect the network at different rates of CAV penetration. The simulation model is carefully designed to match current calibrated models, guaranteeing that the overall network demand faithfully reflects actual patterns. Utilizing historical data from transportation authorities, the system recognizes and imitates several event and incident categories, offering a practical basis for enhancing traffic management response strategies. Most importantly, this strategy complies with regulations set forth by the transport authorities, including safety criteria and possible limitations on traffic rerouting to other routes. The simulation model is an intricate entity in and of itself, covering a large study area and providing a thorough investigation of M30 traffic using both macroscopic and mesoscopic models. This entails incorporating traffic signal plans, precisely identifying CAVs in the simulation, considering connection assumptions, and providing thorough route assistance. Interestingly, the approach uses hierarchical traffic management stations to supervise the entire CAV scenario, but it also includes decentralized control for CAVs. In addition, the approach comprises a thorough feasibility check and the establishment of key indicators to evaluate the impact of events, rerouting techniques, and CAVs. This all-encompassing approach guarantees a comprehensive assessment of the viability and effectiveness of the suggested system in maximizing traffic control and safety, both inside the city of Madrid and in larger urban environments.

We have considered the following presumptions: Our fleet consists of completely autonomous and connected vehicles or CAVs, that may be controlled by the TMC through centralized control. We also consider the fact that the TMC is aware of the origin and destination of every CAV, and that there are one or more pre-established routes that connect each origin and destination. We have considered mixed traffic scenarios in this challenge. The goal is to optimize both the traffic control plan on a particular arterial of the considered network and the path assignment for the entire fleet of Unmanned Aerial Vehicles (UAVs) based on several performance metrics that we will specify below (for each OD-pair and path, define the percentage of CAVs that follow that path).

3.1.3 Progress of the work performed

To formulate the problem at hand, we consider Π to be the entire path set in the network and π_{od} is the path set between an origin o ($o \in O$) and a destination d ($d \in D$), where O and D are the sets of origins and destinations, respectively. From the above assumption, we can say, $\pi_{od} \subseteq \Pi$. V_{od}^{Conv} and V_{od}^{CAV} are the total demands for conventional vehicles and CAVs for OD pair (o, d) $o \in O, d \in D$. The problem can be formulated as follows:

$$\min_{\left(\psi_i^{CAV}, x=(CL,GT,\theta)\right)} F_{svcc} = w_1 * f_{em} + w_2 * f_c + w_3 * f_{TT_{diff}} + w_4 * f_{ec} \qquad (1)$$

Here, Equation (1) is the objective function of this optimization problem and w_1, w_2, w_3, w_4 are combination weights provided by the user and ideally $w_1 + w_2 + w_3 + w_4 = 1$. $\psi_{\pi_i^{CAV}}$ $(0 < \psi_{\pi_i^{CAV}} \leq 1)$ is the fraction of the total respective demand for CAVs for path i .

$$s.t. CL_{min} \leq CL \leq CL_{max} \quad (2)$$

$$0 \leq \theta_z < CL, \forall z \in Z \quad (3)$$

$$GT_{min} \leq GT_{z,i} \leq GT_{max}, \forall z \in Z, \forall i \in I_z \quad (4)$$

$$GT_{z,1} + GT_{z,2} = GT_{z,5} + GT_{z,6}, \forall z \in Z_{rb} \quad (5)$$

$$GT_{z,3} + GT_{z,4} = GT_{z,7} + GT_{z,8}, \forall z \in Z_{rb} \quad (6)$$

$$\sum_i GT_{z,i} = 2CL, \forall z \in Z . \qquad (7)$$

In the signal timing optimization problem, decision variables are cycle length CL, green timings GT and offsets θ. Here x represent the tuple (CL, GT, θ). The problem is constrained by the linear constraints associated with the CL, GT, and θ Equation (2-7). Arterial intersections have the National Electrical Manufacturers Association (NEMA) phase number on them and the time sequence of phases might be organized using the ring-and-barrier diagram, which separates conflicting traffic streams in major and minor street movements. Here, Z is the set of selected intersections in the network for which the traffic plan is optimized and I_z is the NEMA phases for the intersection $z \in Z$. The value of offset for each intersection can vary from zero up to the selected cycle length, the first intersection in the considered path is established as the reference point thus it is associated with zero offset. The last three constraints make sure no conflicting phases are running together, these constraints enforce the ring-and-barrier diagram to the arterial intersection, for the subset of intersections that implement the type of traffic plan, that is defined by $Z_{rb} \subset Z$. Those three constraints apply to those intersections where there are conflicting phases present (like arterial intersections).GT_{min} and GT_{max} are the minimum and maximum duration of green time admissible.

In Equation (8), f_{em} denotes the total emission of the network where $em_{i,x}$ and $em^{*}_{i,x}$ are the emission for CAVs and conventional vehicles for path i with signal timing parameters set x, respectively. $\psi_{\pi^{CAV}_{od,i}}$ and $\psi_{\pi^{Conv}_{od,i}}$ are the fractions of the total respective demand for CAVs and conventional vehicles for path i.

$$f_{em} = \sum_{o\in O}\sum_{d\in D}\sum_{i\in\pi_{od}} \psi_{\pi^{CAV}_{od,i}} \cdot V^{CAV}_{od} \cdot em_i(x) + \sum_{o\in O}\sum_{d\in D}\sum_{i\in\pi_{od}} \psi_{\pi^{Conv}_{od,i}} \cdot V^{Conv}_{od} \cdot em^{*}_i(x)\,. \quad (8)$$

In Equation (9), f_c denotes the congestion at a selected road segment s, where s is a subset of the set S which holds all the paths in the network and f_c is defined by the time difference between free-flow travel time and current travel time for selected s with signal timing parameter set x.

$$f_c = \sum_{s\in S} Delay(s,x)\,. \quad (9)$$

In Equation (10), $f_{TT_{diff}}$ denotes the total travel time difference between CAVs and conventional vehicles, where $TT^{CAV,od}_{i,x}$ denotes the travel time for CAVs for path i in the (o,d) pair considering the signal parameters x, $TT^{Conv,od}_{i,x}$ is the same as $TT^{CAV,od}_{i,x}$, but for conventional vehicles.

$$f_{TT_{diff}} = \left| \sum_{o\in O}\sum_{d\in D}\sum_{i\in\pi_{od}} TT^{CAV,od}_{i,x} - \sum_{o\in O}\sum_{d\in D}\sum_{i\in\pi_{od}} TT^{Conv,od}_{i,x} \right|. \quad (10)$$

Finally, f_{ec} denotes energy consumption of CAVs and is formulated by Equation (11), $e_{i,x}$ denotes energy consumption of a single CAV (we assume the CAV fleet is homogeneous) deployed in path i with signal parameter set x.

$$f_{ec} = \sum_{o\in O}\sum_{d\in D}\sum_{i\in\pi_{od}} \psi_{\pi^{CAV}_{od,i}} \cdot V^{CAV}_{od} \cdot e_{i,x}\,. \quad (11)$$

The proposed CAV route distribution optimization scheme operates in a multi-level control strategy where for a specific OD pair all the possible paths are known before the commencement of the journey and the central TMC distributes the total demand for that OD pair among those paths based on the predefined KPIs. Now this scheme also houses the idea of having distributed control via strategically placed roadside units (RSUs) which can monitor segments of paths between the OD pair and can communicate with the vehicle using the V2I principle. In case of any disruption on the path that RSU is monitoring it can dynamically re-route the vehicle to alternative path for the same OD pair by communicating with the vehicle. In the case of one RSU monitoring path segments for multiple OD pairs, it can correctly propose the most feasible alternate path segment for the corresponding OD pair.

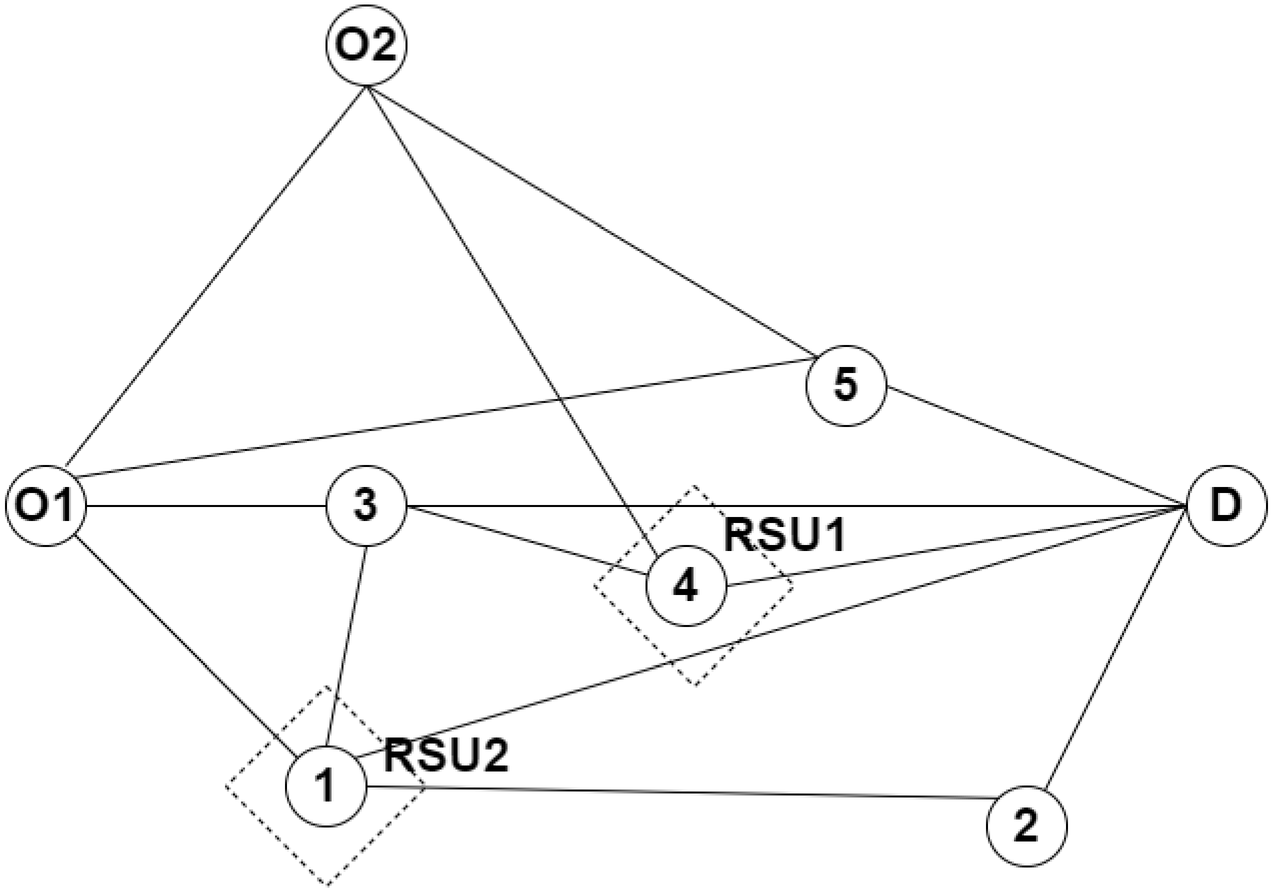

Figure 3 Multi-level control scheme for CAV routing

We can have an example of the above-discussed scheme by using Figure 3, where, let us assume we have a finite demand for the OD pair O1D and the possible paths for this trip are {{O1,1,2,D}, {O1,1,D}, {O1,1,3,4,D}, {O1,1,3,D}, {O1,5,D}, {O1,O2,5,D}, {O1,3,D}}. Lets assume that node {4} and node {1} are RSUs. Now at the beginning of the journey the total demand will be distributed among those paths based on the current status of the transport network and KPIs. In case of any disruption to any path for example say in path {O1,3,4, D} the road is blocked due to some reason then the RSU stationed at node {4} can communicate the alternate route {O1, 3, D} to the approaching vehicle.

Using this distributed control scheme, we can achieve higher throughput from the transport network and the system will also get some degree of transport resilience.

3.2 Social routing

Travel demand management measures can be implemented as an alternative or alongside supply-side measures to improve the distribution of demand over transport networks (see, e.g., Drabicki et al. 2023; Halvorsen et al. 2016; Ma & Koutsopoulos, 2019; Morandi, 2023). Interventions concerning the supply are typically taken for the longer term and can therefore only slowly react to sudden and unexpected changes in the environment. Moreover, measures such as building new or expanding current infrastructure can have counter-productive effects, including a deterioration in network performance as illustrated by the well-known example of Braess. In the context of public transportation, adaptations in the supply might not even be permitted by public transport authorities.

Travel demand management measures, on the other hand, allow for personalized or group and situation-specific interventions on different levels. In this respect, we can roughly distinguish between "hard" and "soft" demand management measures (Bamberg et al., 2011). We define hard travel demand management measures as policies and solutions that directly influence the cost or utility of a travel option, typically through monetary incentives or other types of rewards such as goods and points. Various pilot projects have been conducted to change human behaviour for the common good, not only in the transportation domain (Knockaert et al. 2012; Fioreze et al. 2020), but also to reduce energy consumption (Handgraaf et al. 2013), and to prevent an overload of submissions of farmers (Dirkmaat et al. 2023). Where hard measures may yield a positive impact initially, it "…may change what was initially a moral or social issue (i.e., acting for the greater good) into an economic trade-off with small monetary gains" (pp. 86-87, Handgraaf et al., 2013), and it may thus be difficult to have sustained effects when the rewards are no longer provided. The soft measures, on the other hand, make travellers reconsider their travel behaviour on a voluntary basis – and may therefore be more effective than hard incentives (Ariely, 2016; Handgraaf et al. 2013). Examples include social rewards and voluntary behaviour change initiatives (e.g., Taylor, 2007) to motivate people to choose more sustainable modes of transport through the provision of personalized information (Bamberg & Rees, 2017), to promote off-peak travel (Haloversen et al. 2020) or to take a social route (van Essen et al. 2020). It can be concluded that soft measures aiming for the social behaviour of people by means of information, advice or social rewards offer opportunities in the context of travel demand management.

3.2.1 Proposed innovation

In this section, we propose a framework for the design of social travel advice strategies (or: social rerouting), where a portion of travellers is asked through personalized travel advice to make individually sub-optimal yet acceptable travel choices for the common good. This is a soft travel demand management measure that with the potential to improve demand distribution from a system's perspective. In fact, the boundedly rational decision-making processes of individuals (see Section 2.2) suggest that travellers have a certain flexibility in their travel (see also Henn et al. 2011), and thus may comply with advice as long as the loss or sacrifice in utility is within certain bounds (the indifference band). In a traffic and transit assignment context, this means that the network can be steered away from the user equilibrium to a state which is closer to the system optimum. However, where the system optimum requires significant sacrifices that cannot be expected on a regular basis, or without substantial compensation, the resulting demand distribution can be achieved and maintained over time. Respecting the indifference band, however, is a delicate task since the realized travel conditions on the suggested path need to be anticipated yet are influenced by the choices of all travellers (crowding, queuing, congestion, etc.). Hence, conditions do not only depend on the choices of those who receive and comply with the travel advice, but also on other travellers re-evaluating their travel choices in the long run due to the changing choices of others (Eikenbroek et al. 2022). This complex feedback mechanism needs to be explicitly incorporated to ensure that compliance is maximized, and projected effects are achieved (Ben-Akiva et al. 1991). Therefore, we adopt a hierarchical, bi-level framework, basically a representation of a game between two players (Josefsson & Patriksson, 2007). The upper level represents the authority concerned with network performance, while the lower level (the travellers) is concerned with the individual utility according to a (user) equilibrium. The authority seeks for a strategy to improve the distribution of the demand at the upper level and uses a model (traffic or transit assignment) to predict the behavioural responses. These responses make the ('behaviour' of the) related optimization problem very difficult to analyze and numerically solve for larger network instances, see Angelelli et al. (2020, 2021) and Eikenbroek et al. (2018, 2022.) reactive settings that do not anticipate the travel conditions (Angelelli et al. 2016; Bagloee et al. 2017, Jahn et al. 2005, and Van Essen et al. 2020).

3.2.2 Specifications

The proposed CCAM strategy aims for improved transport system performance through network load balancing and dynamic optimization. More specifically, we develop strategies for social rerouting and cooperative intelligent traffic signal control with freight signal priority. Social travel advice suggests socially beneficial travel choices to receptive travellers but needs to balance the interests of society, individuals and relevant actors to ensure that network performance is improved while user-induced constraints are met. Within CONDUCTOR, cooperative intelligent traffic signal control focuses on the real-time optimisation and coordination of a sequence of traffic signals in a peri-urban setting for the benefit of network efficiency and externalities, where a minimum acceptable level of service and safety needs to be ensured for all (road) users to assure that effects can sustain. The latter innovation will be tested using the Almelo road network (Use Case 1 Almelo pilot), while the first innovation will be detailed on a conceptual level in Section 3.2.3. General requirements for improved signal control relate to the guidelines for traffic signal control in the Netherlands, as described by CROW (Wilson & De Groot, 2006), e.g., to ensure safety, a minimum level of service, and a minimum and maximum green, amber and red times for each direction. More specifically for the proposed innovation, technical requirements include:

- an estimation of an indifference band relative to a reference (baseline) scenario;
- the solution requires a prediction of the vehicles' arrival times at signalised intersections along an urban road under virtually all traffic conditions;
- the definition of relevant objective functions (e.g., waiting time, safety, and emissions) for involved actors (e.g., freight operators, municipality, bus operator) in a mixed-traffic environment balancing short and long-term impacts;
- priority strategy able to accommodate multiple priority requests from different transport modes;
- prediction model incorporating feedback loops to anticipate the impact of changes in signal control on LOS for road users;
- forecasts of near-future signal timings, queue lengths and speeds and conversion to individual speed advice.

The innovation benefits from various data sources, including inductive loop detectors, cameras, iTLCs, GTFS, GPS-based real-time locations of trucks and weather information.

3.2.3 Progress of the work performed

We further study the requirement to balance user and social interests, first in the context of a static traffic assignment with fixed demand. Given is a directed traffic network $G = (V, E)$, with V being the set of nodes, and E being the set of directed edges (road, links, or arcs), $e = (i, j)$, with $i, j \in V$. There is a set of origin-destination pairs (OD pairs) $\mathrm{w} = (t_w, s_w) \in \mathrm{V} \times \mathrm{V}$. Each OD-pair $w \in \mathcal{W}$ has a corresponding demand $d_w > 0$, and is connected by a set of simple directed paths or routes $\mathcal{R}_{k}$. The set of $\mathcal{R}$ of all paths in the network is the union of the path sets per OD-pair, i.e., $\mathcal{R} = \cup_{w \in W} \mathcal{R}_w$. A distribution of the demand d is a pair of flow vectors $(f, x) = (f_r, r \in \mathcal{R}; x_e, e \in E)$ so that $\Lambda f = d, \Delta f - x = 0, f \geq 0$, where $\Lambda \in \mathbb{R}^{|\mathcal{W}| \times |\mathcal{R}|}$ is the OD-path incidence matrix, with $\Lambda_{\mathrm{wr}} = 1$ if route r is in $\mathcal{R}_w$, and $\Lambda_{wr} = 0$ otherwise. $\Delta \in \mathbb{R}^{|\mathrm{E}| \times |\mathcal{R}|}$ is the arc-path incidence matrix, defined by $\Delta_{\mathrm{er}} = 1$ if link e is in route r, and $\Delta_{er} = 0$ otherwise.

Each arc e in the network has a corresponding (link) flow-dependent, separable non-negative, continuous, convex and strictly monotone disutility or travel cost function $l_e: \mathbb{R}_+ \rightarrow \mathbb{R}_+$. The route cost

$c_r(f)$, induced by traffic flow (f, x), is the sum of travel costs of all edges constituting that path: $c_r(f) = \sum_{e \in r} l_e(x_e)$.

When concerned with route choice, Wardrop (1952) formulated two criteria to determine the distribution of the demand over a traffic network. Wardrop's first principle assumes travellers to be selfish and perfectly rational in making route choice decisions, and the resulting Wardrop equilibrium is such that all travellers for the same OD-pair face the same minimum route cost. In our context of boundedly rational route choice, a portion of the travellers (so-called social travellers) is willing to comply with social travel advice as long the route is not perceived to be substantially worse compared to the best-possible option (see also Eikenbroek et al. 2022). Therefore, we divide the demand into social and selfish trips. The social trips vector is denoted by $d^s \in \mathbb{R}_+{}^{|\mathcal{W}|}$ and the selfish demand vector is denoted by $d^n \in \mathbb{R}_+{}^{|\mathcal{W}|}$, whereby $d = d^s + d^n$. The set of feasible flow distributions is denoted by $\mathcal{F}$, i.e., $\mathcal{F} = \{(f^s, f^n, x) | \Lambda f^s = d^s, \Delta(f^s + f^n) - x = 0, f^s \geq 0, f^n \geq 0\}$. In our framework, we assume that social travellers are willing to take a detour as long as the route is at most $\varepsilon \cdot 100\%$ worse, $(\varepsilon \geq 0)$, compared to the shortest path (in terms of route costs). Consequently, there is a whole space of 'stable' distributions. Formally, flow $(\bar{f}^s, \bar{f}^n, \bar{x}) \in \mathcal{F}$ with corresponding path cost vector $c(\bar{f}), \bar{f} = \bar{f}^s + \bar{f}^n$, is said to be in mixed equilibrium if for all $w \in \mathcal{W}, r \in \mathcal{R}$, the following conditions hold:

$$\bar{f}_r{}^n > 0 \Rightarrow c_r(\bar{f}) \leq c_q(\bar{f}), \qquad \text{for all } q \in \mathcal{R}_w \tag{12a}$$

$$\bar{f}_r{}^s > 0 \Rightarrow c_r(\bar{f}) \leq c_q(\bar{f})(1+\varepsilon), \qquad \text{for all } q \in \mathcal{R}_w \tag{12b}$$

Intuitively, these two conditions indicate that there is no intrinsic motivation to change routes: selfish travellers travel on a minimum-cost path, while the social travellers travel on an 'acceptable' or 'reasonable' path. Any feasible flow distribution that satisfies the above conditions can be considered 'attainable' and 'maintainable', since all travellers are satisfied with their route. Note that, in contrast to e.g., Di et al. (2017), we adopt here a multiplicative rather than an additive indifference band.

The social travel advice strategy determines the best possible routes to be proposed to the social travellers. The accompanying optimization problem is to minimize an objective function such as total travel time, denoted by $z(f)$, while the resulting flow distribution should be in mixed equilibrium, i.e.,

$$P: \min_{(f^s, f^n, x) \in \mathcal{F}} z(f) \quad \text{s.t.} \quad (f^s, f^n, x) \quad \text{satisfies} \quad (12a), (12b).$$

The f^s– part of the optimal solution of problem (P) is of interest, as it includes the paths to be suggested to the social travelers. Through condition (12b) the travel costs on suggested paths are within bounds compared to the best possible path. The optimization problem (P) is difficult to solve directly and can be classified as a mathematical program with equilibrium constraints (Luo et al., 2010), where standard constraint qualifications may fail to hold at any feasible point. This is mainly because the right-hand side conditions in (12a) and (12b) should solely hold under strictly positive path flows, see Kleinert et al. (2020) for further details.

Social rerouting in public transit networks

In networks without capacity constraints (*uncapacitated)*, the steady-state distribution of the demand over a network is typically modelled along the condition as formulated by Wardrop (1952). Particularly in public transport networks, however, the limited available capacity is a major determinant of travel choices, i.e., vehicle capacities make that a Wardrop equilibrium might not exist (see Corman, 2020; Marcotte et al. 2004; Sheffi, 1985). In this section, we consider a schedule-based transit assignment, with limited vehicle capacities influencing the disutility or generalized cost of travel options as follows. First, passengers fail to board once capacity is reached. Second, there is additional discomfort due to in-vehicle crowding. Consequently, the framework of the previous section does not directly apply to the setting considered here since the travel cost functions basically become non-separable, i.e., the cost explicitly depends on upstream boardings.

We adopt a schedule-based event-activity network to describe the supply of public transport services as a time-extended yet static graph. Here, each node in the graph corresponds to an event, i.e., a time-station/stop combination, for example, the departure or arrival of a train. Each directed edge connects a pair of events, resulting in edges representing activities of access (passengers entering the system from an origin), egress (passengers leaving the system at their destination), driving (movement of vehicles), dwelling (vehicles waiting at stations), and transfer (passengers transferring from one service to another). Further, each arc e has an associated capacity, denoted by κ_e. For driving and dwell arcs, the arc capacity is limited and equal to the maximum vehicle capacity (standing and seated passengers). For the other arcs, we assume that there is no capacity constraint.

Given a timetable, the arc capacities, and a set of multi-period origin-destination pairs, the event-activity graph describes the (dynamic) supply of a schedule or timetable-based transit network. The distribution of demand, now involving mode (e.g., train, bus, tram) and route choices, over the network (the quasi-static transit assignment) cannot be formulated along the lines of Wardrop since it may not exist, hence we need to rephrase the conditions (12a) and (12b) to explicitly account for vehicle capacities. We adopt the (user) equilibrium notion of Correa et al. (2004) to do so. A user equilibrium is defined as the demand distribution where capacity is not exceeded, and each traveller is assumed to be satisfied with their choice in the sense that a unilateral change is either not possible since boarding will be denied or will not lead to an improvement in generalized cost. We introduce therefore ${c^+}_{r\to q}(f)$, the anticipated route cost on q (conditional on f) when unilaterally switching from r to q. This function is, in contrast to $c_r(f)$, no longer continuous but only *lower semicontinuous*, i.e., it 'jumps' to infinity if capacity is reached when a passenger tries to board (see also Bernstein & Smith, 1994). We do not formally introduce this function here, but the function assumes that (i) boarding a service included in q is considered possible if the same service is also included in p, and (ii) boarding might be impossible if capacity is reached, while in practice a passenger might arrive earlier and still be able to board. The latter assumption, however, can be relaxed in a fully dynamic context.

We can generalize the mixed equilibrium conditions of (12a) and (12b). In fact, in our schedule-based public transport setting, flow $(\bar{f}^s, \bar{f}^n, \bar{x}) \in \mathcal{F}$ with corresponding path cost vector $c(\bar{f}), \bar{f} = \bar{f}^s + \bar{f}^n$, is said to be in mixed equilibrium if for all $w \in \mathcal{W}, r \in \mathcal{R}$, in addition to $\bar{x} \leq \kappa$, the following conditions hold:

$$\bar{f}_r^{\,n} > 0 \Rightarrow c_r(\bar{f}) \leq {c^+}_{r\to q}(\bar{f}), \qquad \text{for all } q \in \mathcal{R}_w \setminus \{\mathrm{r}\} \tag{13a}$$

$$\bar{f}_r^{\,s} > 0 \Rightarrow c_r(\bar{f}) \leq {c^+}_{r\to q}(\bar{f})(1+\varepsilon), \quad \text{for all } q \in \mathcal{R}_w \setminus \{\mathrm{r}\} \tag{13b}$$

The optimization problem (P) to determine the best-possible social travel advice is adapted accordingly. For the sake of numerical experiments, problem (P) can be reformulated as a mixed-integer program, and in our case solved using the GUROBI optimization software.

We perform numerical experiments using cases based on the urban public transport network of the Twente region in the Netherlands. Through these experiments we aim to quantify the potential impact of social travel advice strategies on network performance. We specifically consider the bus lines that operate in the municipality of Enschede, where a few lines – particularly from and to post- high-school educational institutions - incidentally experience overcrowding issues.

The case study examines a regular business day, and the scheduled timetable from 07:45 to 08:30, for which we identified 306 major OD pairs (combination of origin stop, destination stop, and desired departure time). We adopted a bureau of public roads-like generalized cost function (Gentile & Nokel, 2016), with the 'free flow' time equal to the scheduled travel time, $\alpha = 1/32$ and $\beta = 4$ for driving and dwelling arcs, to model the in-vehicle disutility as an increasing function of the occupancy. We assume a seating capacity of 40, and an incremental capacity of 80. The other arcs in the network have a fixed cost corresponding to the actual travel time.

We compare a baseline scenario (i.e., user equilibrium), the system optimum, and the demand distribution because of social travel advice using the total generalized costs as an indicator for network efficiency. Figure 4 shows the relative efficiency gain compared to the network performance in user equilibrium, for a range of scenarios regarding the indifference band ε, and the fraction social travelers.

The results in Figure 4 show that in system optimum network efficiency improves by 1.1% compared to user equilibrium. Comparable network performance can be achieved if 70 to 100% of the riders are willing to act socially and are willing to take a detour that is at most 20% worse (in generalized cost) compared to the best-possible available alternative. If social travellers only accept detours of 5 or 10%, the maximum possible improvement in network efficiency is 0.6 and 0.9%, respectively. In case a smaller share of passengers is making socially beneficial travel choices, improvements decrease but, at the same time, the maximum gradient of improvements is the largest under low fractions of social passengers. In fact, for a given acceptable tolerance, 25% of the improvement in efficiency can already be obtained with 20% of the travellers willing to act for society at large.

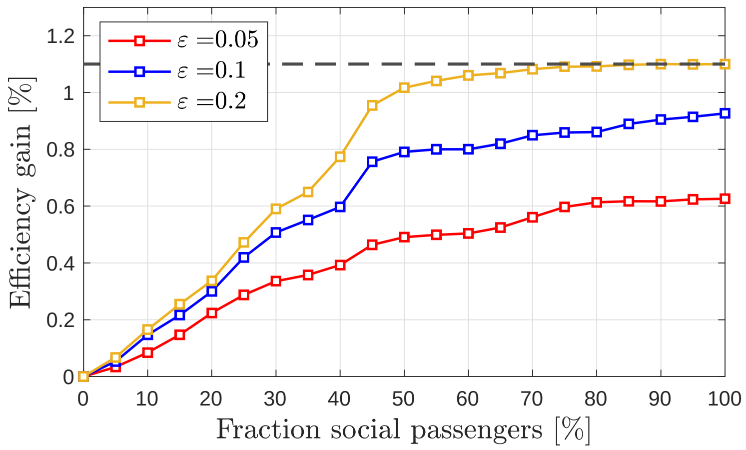

Figure 4 Social Routing

3.3 Prediction models for Demand Responsive Transport

3.3.1 Proposed innovation

The research and technology development will focus on developing algorithms for predicting the demand for specific transport services with reliable metrics. The idea is to provide the "observability" of demand prediction to feed the optimization algorithms for traffic routing & fleet operation. The second part of the development is focused on developing algorithms to process optimization in real-time – processing traffic events in real-time (change in demand, environmental change, etc.). In such a way, the intercity transport infrastructure will augment to gain elasticity and adaptability for real-time DRT services.

To build such a complex model we need concrete and reliable data as well as real-life use cases to test the model. The GoOpti Intercity infrastructure is addressing this challenge. Within CONDUCTOR, GoOpti will provide its IT infrastructure, network of partners and vehicles on the routes Slovenia - Italy, Slovenia - Croatia and Slovenia - Austria to test and demonstrate advanced simulation models in real-life conditions as a DRT service.

3.3.2 Specifications

In this particular use case, our objective is to address the challenge of forecasting expected demand within the context of GoOpti's services. Our primary focus will be on predicting the number of passengers scheduled for drop-off during specific time slots at designated locations. To illustrate, let us consider the scenario of GoOpti's transportation service between location A and location B. The model's task is to anticipate the number of passengers who will be dropped off at location B (picked up on the route from location A) on a given date and time. The expected three routes that will be used in the use case are the following:

- Maribor – Vienna Airport
- Ljubljana – Zagreb Airport
- Ljubljana – Trieste Airport

All three routes are connections to airports located in the neighbouring countries of Slovenia. The forecasting will be applied in both directions from the city to the airport (passengers are travelling abroad) and from the airport to the city (passengers are travelling to Slovenia).

To enhance the accuracy of our predictions, we will leverage various data sources, each providing valuable insights:

- *Weather Information*: Historical weather data, available since 2015, can be integrated into our predictive model.
- *Flight Information*: Commencing from September 2023, we have been collecting data related to flights, enriching our predictive capabilities in the future.
- *Traffic Information*: Data sourced from the Motorway Company in the Republic of Slovenia (DARS) will be utilized, offering valuable insights into traffic patterns.
- *GoOpti Product Orders*: Comprehensive data on GoOpti product orders, accessible since 2014, will serve as a fundamental resource for our modelling efforts.

Before delving into the model training phase, the collected data will need to undergo preprocessing steps. This includes cleaning, aggregation tailored to the specific goal (considering resolution), and the generation of relevant features such as lag, workdays, holidays, weekends, etc. This meticulous preprocessing ensures that the data is well-prepared and suitable for subsequent model training.

Two distinct types of models will be developed, aligning with the characteristics of the available data sources:

1. *Short-Term Prediction Model* (Up to 14 days): This model will harness GoOpti product orders data along with the additional sources (weather, flight, traffic information) to enhance prediction accuracy within a two-week timeframe.
2. *Long-Term Prediction Model* (Up to 1 Year): Focusing on extended forecasting, this model will solely rely on GoOpti product orders data, tailoring its predictions for periods extending up to a year.

By employing this dual-model approach, we aim to provide nuanced and accurate predictions, catering to both short-term and long-term planning needs within the dynamic landscape of GoOpti's transportation services.

The specifications for this use case can be summarized as follows. The task is to train a model for predicting the number of passengers, while fulfilling the following requirements:

- Predictions are limited to passengers' that have a drop-off during specific time slots at designated locations (defined by predetermined routes explained above).
- The pickup or drop-off needs to be considered as originating from the city if the actual location is located within 30 km of the city centre.
- The predictions need to be made for both directions of the route.
- The prediction resolution will be predefined (1 hour or more).
- Data that can be used for training and testing of the models is limited to GoOpti's own historical data in potential combination with weather, flight, and traffic information.
- Two types of predictions are expected, short term up to 14 days and long term up to 1 year.

3.3.3 Progress of the work performed

In the ever-evolving landscape of data analytics and predictive modelling, various methodologies have been rigorously researched and evaluated to identify optimal models for forecasting tasks. Among the prominent contenders, XGBoost, Random Forest, Neural Networks including LSTMs and WaveNet, Wavelets Features, Linear Regression, Koopman Analysis, and treating the problem as zero-inflated regression with a 2-fold approach have emerged as leading techniques for predictive analytics across diverse domains. These models have been extensively studied and scrutinized, aiming to harness their unique capabilities in handling complex datasets and providing accurate predictions. Through a careful examination of their underlying principles, distinct features, and empirical performance, we have sought to uncover their respective strengths and limitations. The main characteristics of the mentioned approaches are the following. XGBoost stands out for its regularization techniques that reduce overfitting and its capacity to handle missing data. It also has the ability to handle a variety of data types and has been widely used in various machine learning competitions. Random Forest is known for its ability to handle large amounts of data, high dimensionality, and the potential to deal with missing values. It also provides a measure of variable importance, making it useful for feature selection. LSTMs are known for their ability to capture long-term dependencies in sequential data and are commonly used in tasks such as natural language processing and time series analysis. WaveNet, on the other hand, is specifically designed for generating high-quality raw audio waveforms, making it highly effective in applications like speech synthesis. Wavelet analysis allows for multi-resolution analysis of signals, enabling the identification of localized changes in data both in the time and frequency domains. This makes it effective for analysing signals with non-stationary and transient characteristics. Linear regression is simple and easy to interpret, making it a popular choice for initial modelling. It provides coefficients that represent the relationship between the dependent and independent variables, enabling the understanding of the direction and strength of the relationship. Koopman analysis provides a way to study the dynamics of complex nonlinear systems through a linear framework, enabling the use of powerful linear tools for analysis and control. It allows for the understanding of the underlying dynamics and behaviour of complex systems. The 2-fold approach likely involves an initial step of identifying excess zeros and a subsequent step for modelling the remaining count data. This approach enables the accurate modelling of data with excessive zeros, providing more reliable estimates and insights compared to traditional regression methods.

In the realm of predictive modelling and time-series analysis, the utilization of diverse features plays a crucial role in enhancing the accuracy and robustness of forecasting tasks. Among the array of feature types, certain key elements have garnered significant attention for their ability to capture temporal dynamics and contextual nuances within the data. Lag features, instrumental in encapsulating historical trends and patterns, enable models to account for past dependencies and temporal relationships. On the other hand, the incorporation of holiday features allows for the consideration of specific dates with exceptional societal or cultural significance, facilitating the modelling of unique behavioural shifts or anomalies associated with these events. Furthermore, the inclusion of date features, encompassing various temporal components like the day of the week, the week of the year, or the time of day, equips models with the capability to discern recurring patterns and seasonality, thereby enhancing the comprehension of temporal variations and cyclical trends. Additionally, the integration of moving average features aids in smoothing out short-term fluctuations, emphasizing long-term trends, and mitigating the impact of noise, ultimately facilitating a more refined understanding of underlying patterns and trends within the data. Leveraging these diverse feature types collectively contributes to a more holistic and nuanced approach in predictive modelling, empowering analysts to derive more accurate and insightful forecasts for a wide range of applications.

In the realm of data pre-processing for complex analysis tasks, several key techniques have emerged as instrumental in refining the data to ensure optimal model performance and accurate insights. Scaling, a pivotal pre-processing step, facilitates the standardization of numerical features, ensuring that they are on the same scale, thereby preventing any particular feature from dominating the learning process due to its larger magnitude. This crucial process aids in stabilizing model convergence and enhancing the interpretability of the resulting analyses. Detrending, another essential pre-processing technique, involves the removal of underlying trends or patterns from the data, enabling the isolation of the core fluctuations and variations that are of primary interest. By eliminating long-term trends, detrending helps focus the analysis on the inherent cyclical and seasonal components, thereby facilitating a more accurate understanding of the underlying dynamics and fluctuations within the data. The identification and removal of outliers assume paramount significance. By systematically detecting and eliminating anomalous data points that may skew the analysis, outlier removal ensures that the resulting insights accurately reflect the actual trends and patterns in the data. Particularly in cases where anomalies or data inconsistencies may arise due to reporting errors or irregularities, the application of outlier removal techniques is crucial in maintaining data integrity and fostering a more accurate assessment of the trends. Employing these pre-processing techniques collectively serves to enhance the robustness and accuracy of data analyses, empowering researchers and analysts to derive meaningful and reliable insights from complex and dynamic datasets.

In the pursuit of forecasting with a horizon extending up to one year ahead, an extensive analysis of the above-mentioned diverse forecasting models, feature engineering techniques, and pre-processing methodologies is being performed with the goal of capturing the intricacies and dynamics inherent to the data. Furthermore, we are also exploring hierarchical forecasting methodologies that can enrich the forecasting process, enabling the hierarchical modelling of complex data structures and the generation of forecasts at various aggregation levels. Through consequent comprehensive analysis of multi-level forecasting hierarchies, this approach can provide a holistic understanding of the interdependencies and interactions within the data, empowering analysts to generate accurate and granular forecasts for diverse forecasting horizons, including the extensive one-year horizon.

Collectively, the integration of these advanced forecasting models, feature engineering techniques, pre-processing methodologies, and hierarchical forecasting approaches has culminated in a comprehensive collection of data for conducting multi-horizon forecasting tasks, enabling the derivation of accurate and insightful predictions on forecasting tasks extending up to one year ahead.

The research and evaluation of all these approaches are still ongoing, continually exploring the most intriguing avenues and developments within the field of forecasting. With the ever-evolving landscape of data science and predictive analytics, the investigation of these methodologies remains dynamic, driven by a persistent quest to uncover novel insights and advancements that can further refine and enhance the predictive modelling process. As we delve deeper into the intricacies of these forecasting models, feature engineering techniques, and pre-processing methodologies, we continue to uncover new possibilities and refine existing approaches, aiming to unlock greater predictive accuracy.

3.4 Optimisation techniques for urban logistics

The demand of urban goods delivery has increased in the last ten years. The adoption of e-commerce is responsible for this shift of traffic due to last-mile delivery. To manage and balance this urban traffic bump CONDUCTOR will investigate and propose solutions for last-mile delivery based on the integration of urban distribution of goods with DRT.

3.4.1 Proposed innovation

In this section solutions for the integration of urban logistics into a DRT system are proposed. To that end, two different approaches to this problem will be developed by Deusto and TUM. To test and validate the approaches, simulations are to be performed. Therefore, two different simulation tools are provided by Aimsun, Aimsun Next and Aimsun Ride, that will support the solutions from TUM and Deusto, respectively. The demand data needed is generated by Nommon, which is developing two models to characterise professional and last-mile delivery trips and to estimate the DRT demand, which will be used as inputs for the simulations.

This activity will investigate and design urban logistics networks with potential intermodality, making use of data from the logistics sector combined with sources of information on mobility and activity of the population and its processing using different optimisation algorithms.

The service will address solutions aimed at the optimal integration of DRT for urban freight distribution. For that, in first place the DRT demand is estimated. To that end, Nommon is developing an algorithm whose goal is to estimate the demand for DRT with CCAM (DRT-CCAM). Since there are currently no CCAM services in urban areas, the demand for carsharing services is used as a proxy of the demand for DRT-CCAM services, as these are considered the most likely candidates to evolve into DRT-CCAM when they become a reality (Narayanan et al., 2020).

Prior to the development of the DRT-CCAM demand estimation model, a literature review was performed to identify the user's sociodemographic characteristics related to the CCAM acceptance and adoption (see deliverable D1.1 Report on stakeholder requirements, user needs and social innovations). Some of these user characteristics (namely, age, gender, and income level) are considered for the estimation of DRT-CCAM demand. To improve this characterisation, the user's profile will be enriched with additional sociodemographic information to include two more features: household size and car ownership, which are also relevant for adoption.

This approach will allow estimating demand for different levels of CCAM penetration. Using this estimation, we will identify valley demand hours for certain DRT-CCAM services, which can be used by logistic operators to deliver their goods.

Next, the urban freight delivery is integrated into the DRT-CCAM service. The DRT users are assumed to always announce their OD pair dynamically and they need to be picked up within a maximum waiting time to maintain certain service quality. On the other hand, the freight requests are assumed to be significantly less time-critical. The main challenge is how to dynamically form vehicle routes that pool passenger requests and simultaneously deliver (or pickup) freight without significantly compromising the service quality of passengers. The overall problem complexity is further increased by longer service time windows of the freight requests. Practically, freight requests would at least require certain time estimations (ranging in hours) to make sure that handlers of the freight are available during the time window. Thus, we will also investigate how time-window estimations for freight requests could be incorporated into the developed optimization method. The impact of above solutions on the overall transport network (e.g., average travel times, total vehicle travelled distance, total vehicle travel time, and total vehicle emissions, indicators that are expected to be reduced by this strategies), in particular for the area of the Madrid ring road where the Aimsun Model is deployed, see Urban logistics Use Case (UC3) description in deliverable D1.3 (Detailed use-case specification and their KPIs) for more details), will be evaluated supported by the Aimsun simulator platform and considering different demand-supply balancing strategies aiming at the optimisation of the performance of the overall transport network.

3.4.2 Specifications

The solution aims to obtain an algorithm for the distribution of goods and people, and we need to dispense with a transport model that allows the simulation of route optimisation models. There are some general requirements to be met by the solution obtained, among them:

- The solution must ensure the safety of freight and passengers.
- The solution must comply with existing transport rules and regulations.
- The solution must ensure that passenger transport timetables are adhered to, and that people's mobility is prioritised.
- The solution must adhere to the delivery window of the shipments.

There is also a set of requirements that can be considered for simulating the solution, which can allow us to verify the correct functioning of the proposed algorithm and possible improvements in parameter adjustment. It would be important to have prior knowledge of the expected demand and the different passenger transportation services and their schedules. In this sense, having a detailed understanding of the last-mile goods delivery service operation model is crucial. Additionally, the indicators that allow measuring the impact of the obtained solution are among the main requirements to define.

For the implementation of the proposed solution in a real case we must consider the following requirements:

- Governance would be necessary to ensure the regulation of the different services and the interaction between the parties.
- Cooperation and understanding on the part of freight logistics operators and passenger transports.
- Security and protection of the system against cyber-attacks and critical infrastructures, whereby the system obtained must comply with security and cyber-security standards.
- Adaptation of the vehicle infrastructure to enable mixed passenger and freight transport.
- Orchestrate a secure system of information transfer between the different stakeholders.

3.4.3 Progress of the work performed

In accordance with the established work plan and framed especially in task T3.4: Dynamic optimization, the analysis and design tasks of the optimization techniques that support the proposed innovation and the Use Casa 3 have already begun with an exhaustive analysis of the techniques reviewed in Section 3.4.2 and the definition of the models relevant in the context of CONDUCTOR.

Two models were proposed based on the experience in solutions for transport optimization provided by Deusto and TUM. Both systems will be an evolution of existing developed solutions (Deusto's Optimization Engine and TUM's FleetPy).

The main differences between FleetPy and the module from Deusto are related to demand modelling and time constraints. FleetPy allows modelling and defining the demand for both types of transport services whereas in the system developed by Deusto disaggregated demand for both people and goods is a required input, expected to come via demand models generated by Nommon. Also, FleetPy doesn't consider the "time window" constraint for the pick-up of deliveries, however Deusto's module does. This can be one of the main differences between both solutions, and after testing them in Use Case 3, the results of both modules can be assessed.

Additionally, the CCAM demand model proposed by Nommon is also described in this section, as a preliminary step for Deusto's Optimization Engine. A dedicated description of the proposed systems, with a comprehensive characterization of the model's main modules is presented in the following subsections.

3.4.3.1 Demand prediction for coordination with parcel delivery

Nommon is developing a software solution for the characterisation, estimation, and prediction of urban passenger transport demand for new connected and autonomous DRT services. This development is aimed at providing a plausible passenger demand estimation of CCAM-enabled DRT services for different penetration levels of CCAM. This demand estimation will be used to identify passenger demand-valley periods for which the service overcapacity can be used for last-mile delivery and the design of optimal strategies for the coordinated transport of passenger's and goods under different future scenarios.

3.4.3.1.1 Data used

Given that there are currently no CCAM services in cities, the characteristics of the demand for DRT-CCAM trips are approximated using shared mobility demand data. Specifically, these correspond to demand data for carsharing services, as they are seen as the most likely candidates to evolve into DRT-CCAM when such services become available. Carsharing demand data is provided by an aggregator of trip data from shared mobility services. These data are described hereon in the present document, as they had not been purchased yet at the time of the delivery of D1.2 (Specification of the future mobility system and data sources) document in which they should have been included.

The information provided the number of trips, number of available vehicles, number of vehicles used by city and day, geolocation information of the vehicles and information on the trips performed by the vehicles in the city (start and end complete date, distance and start and end coordinates). Carsharing data to be used in this project covers all the car-shared mobility services in Madrid Region for a whole year (from June 2022 to May 2023, both included). These car-shared mobility services are:

- Voltio, for which data in the Madrid Region are available from 2023-02-14.
- Free2move, for which data in the Madrid Region are available from 2022-08-12.
- Goto, for which data in the Madrid Region are available from 2022-12-09.
- Sharenow, for which data in the Madrid Region are available from 2022-03-15.
- Wible, for which data in the Madrid Region are available from 2020-12-06.
- Zity, for which data in Madrid Region are available from 2020-12-06.

Each of these services has a different area of operation (geofence) in the Madrid Region. Most of Madrid inner ring road urban area is covered by all 6 services. Figure 5 shows the area of operation of Voltio carsharing service in Madrid, as stated on their website, as an example.

Figure 5 Voltio carsharing service area of operation in Madrid Region (Voltio website)

Carsharing demand data are complemented by additional data from shared mobility services, public transportation, general mobility matrices (from mobile network data MND), weather patterns, socio-demographic information and land use data to achieve more accurate characterisation, estimation and prediction of passenger transport demand for new connected autonomous DRT services. See Deliverable D1.2 (Specification of future mobility system and data sources) for more details on these data sources.

3.4.3.1.2 Methodology

3.4.3.1.2.1 Carsharing demand prediction model

Firstly, a machine learning prediction model for carsharing services demand is trained with carsharing historic demand and data from other sources. This prediction shall be disaggregated at least at an hourly level to find valley periods of demand in subsequent developments.

Due to the limitations in the areas of operation of each carsharing service, this model can only be trained with data from the areas covered by carsharing services in the Madrid Region. The main characteristics of each zone within this area of operation are considered (land use, general mobility demand, population density, socio-demographics, etc.) to train a model that is able to predict carsharing demand to/from zones outside of the areas of operation of the considered carsharing services. This demand prediction will subsequently be pondered based on various DRT-CCAM penetration scenarios.

The steps for the calibration and application of the ML model predicting carsharing demand are shown in Figure 4 and described below:

1. **Initial analysis, pre-processing and cleaning**: the first step is to analyse and clean the data to remove outliers (e.g. records of trips with unreliable speeds, etc.) and identify and or correct missing values. After this, data standardization is performed to facilitate data fusion, feature analysis and model training.
2. **Trip volume normalisation**: since each of the carsharing services in the data has a different geofence or area of operation, a spatial trip volume normalisation is needed. Some areas may be underrepresented in the data, while some may be overrepresented, depending on the service availability. After applying this normalisation, the result corresponds to the real

carsharing demand, which is the addition of the satisfied carsharing demand and the latent carsharing demand.

3. **Data fusion**: the real carsharing demand data is fused with external context data such as land use, population, socio-demographics, general mobility OD matrices from MND, etc. This allows to take into consideration external features for the prediction model training.
4. **Train and fit prediction model**: the fused data is inputted to a machine learning regression model that predicts the volume of carsharing trips between each pair of zones for a specific time period according to the characteristics of both zones and the historic demand data. Several ML models will be designed and trained in order to find the ones with the best accuracy.
5. **Use model to predict new data**: once the model has been trained and validated and has achieved the required accuracy metrics, it will be ready to be fed new data and make predictions of the carsharing trips given a set of zones and time periods.

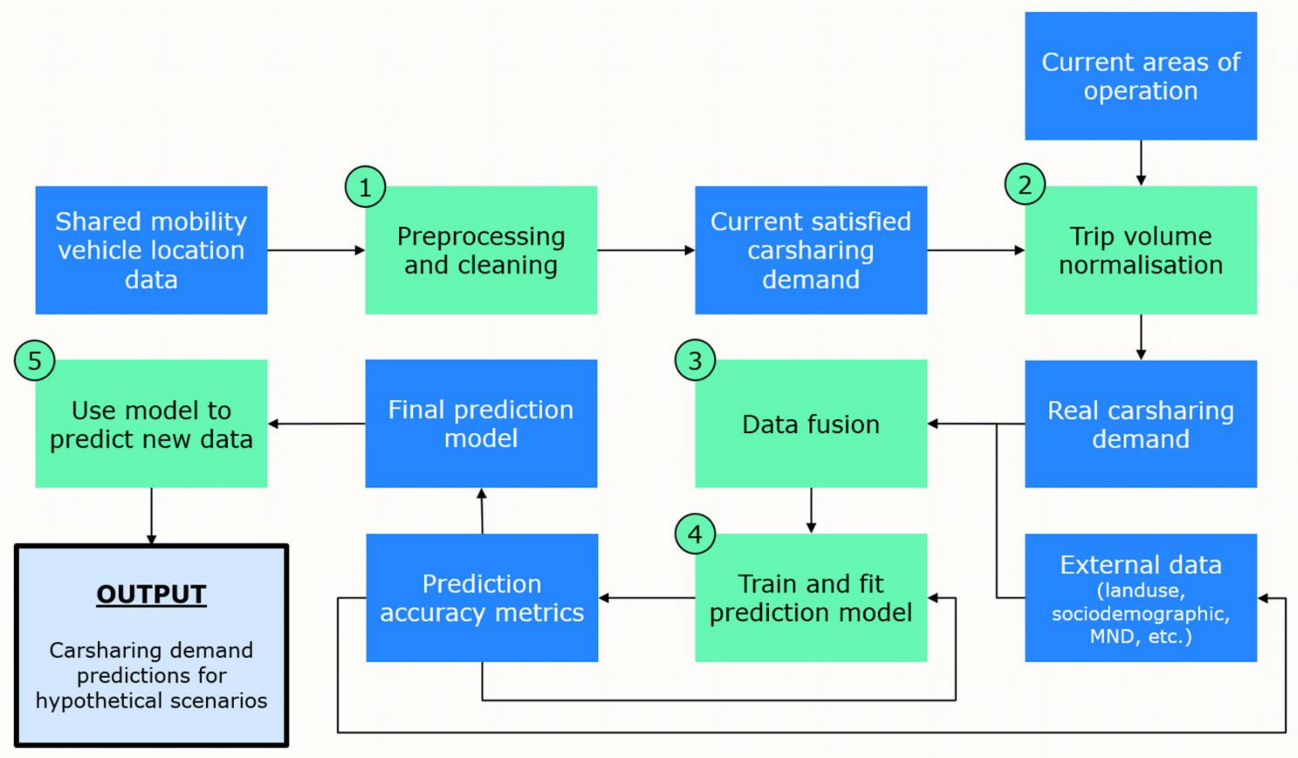

Figure 6 Carsharing demand prediction model methodology flowchart

3.4.3.1.2.2 DRT-CCAM penetration scenarios

Once a model that accurately predicts carsharing demand is built and working, the next step is to formulate various scenarios for DRT-CCAM penetration based on the carsharing demand predictions to obtain the DRT-CCAM target services demand.

Various scenarios for DRT-CCAM penetration will be formulated and crafted based on observed travel patterns and user characteristics deduced from the predicted carsharing demand.

To enhance the characterization of demand, user profiles may be further enriched with socio-demographic data specific to CCAM usage, included in other developments. This enrichment process involves merging MND with survey data through machine learning techniques to extract key features that had been identified as relevant for DRT-CCAM adoption in deliverable D1.1 (Report on stakeholder requirements, user needs and social innovations), such as household structure and car ownership.

3.4.3.1.3 Technical implementation

The carsharing demand prediction will be achieved through a supervised regression machine learning model. Different models will be tested in order to find the ones that adapt best to this specific prediction problem. Among the models to be tested are those commonly used for analysing temporal series, such as ARIMA or SARIMA ((seasonal) auto-regressive integrated moving average), alongside more generalized models like random forest, gradient boosting, and support vector machine.

RFE (recursive feature elimination) will be used in order to find the relevant features that influence on the values to predict. RFE iteratively trains models with different feature sets, systematically identifying those that bear no impact on model accuracy and subsequently discarding them.

Hyperparameter tuning will be performed to find the model parameters that provide the best model accuracy, without compromising performance or runtime.

Following standard data science practices, the data will be split into three datasets: train, validation, and test. The training set will be used to train the model, the validation set will assist in fine-tuning parameters, and the test set will serve to evaluate the model's performance on unseen data.

Depending on the model's performance and dataset volume, cross-validation might be incorporated. Cross-validation involves partitioning the dataset into complementary subsets, iteratively using different subsets for training and validation to maximize the use of available data while evaluating model performance across multiple splits.

Several accuracy metrics will be used to evaluate the models' performance, including R-squared and mean absolute percentage error. These metrics will provide insights into the model's ability to explain variance and the percentage-wise accuracy of predictions, respectively, and may be used to compare the accuracy of different models both with train and validation data.

3.4.3.1.4 Preliminary analysis

This section shows the key insights from the carsharing demand exploratory data analysis.

The carsharing demand data covers a whole year, in which there is a high variability of trip volume per month, as seen in Figure 7:

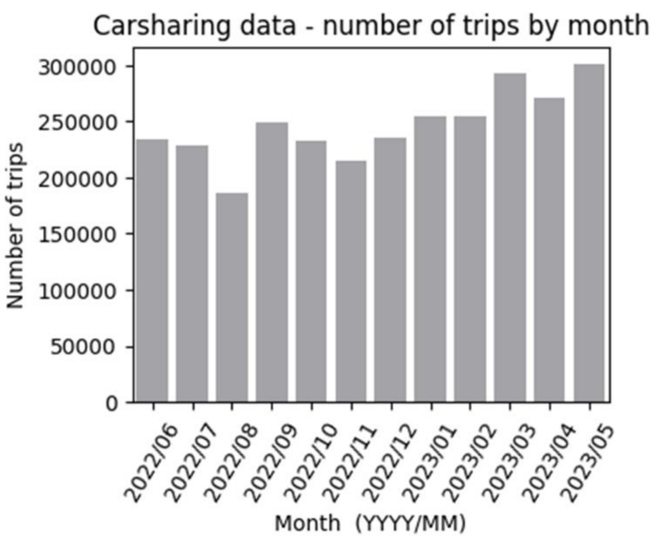

Figure 7 Carsharing trip volume by month

Figure 8 shows the data segmented by date for four specific months. The initial month (September 2022) serves as a standard representation without any significant festivities. In this month, a discernible trend emerges: carsharing services demonstrate reduced usage on Sundays, steadily increasing throughout the week and reaching peak usage levels, on Fridays.

The impact of festivities becomes apparent in the 2023/04, 2022/12 and 2022/08 subplots of Figure 8 where non-working days consistently correlate with decreased carsharing trip values. Additionally, August's general pattern stands out notably, exhibiting significantly fewer trips compared to non-summer months.

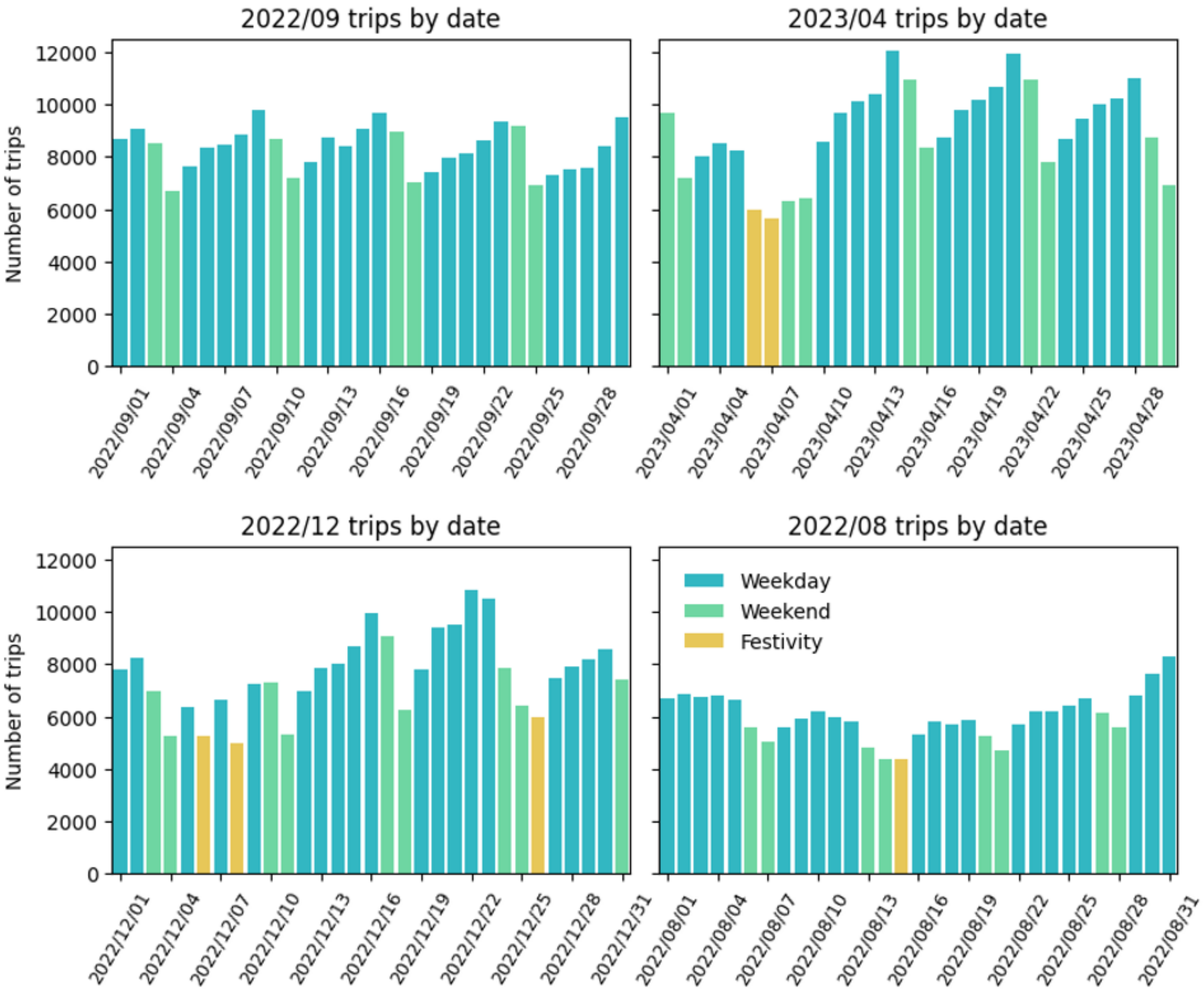

Figure 8 Carsharing trip volume by date for September 2022, April 2023, December 2022 and August 2022

Analysing the carsharing demand data across hourly periods, Figure 9 reveals distinct peaks during morning, afternoon, and evening times as depicted in the graphs, which correspond to the expected typical urban transport demand peaks. Interestingly, the morning peak registers a lower volume of trips compared to the evening peak. This is probably because these services are predominantly utilized for non-work/non-study-related leisure trips, whereas the morning peaks are associated with mandatory commuting.

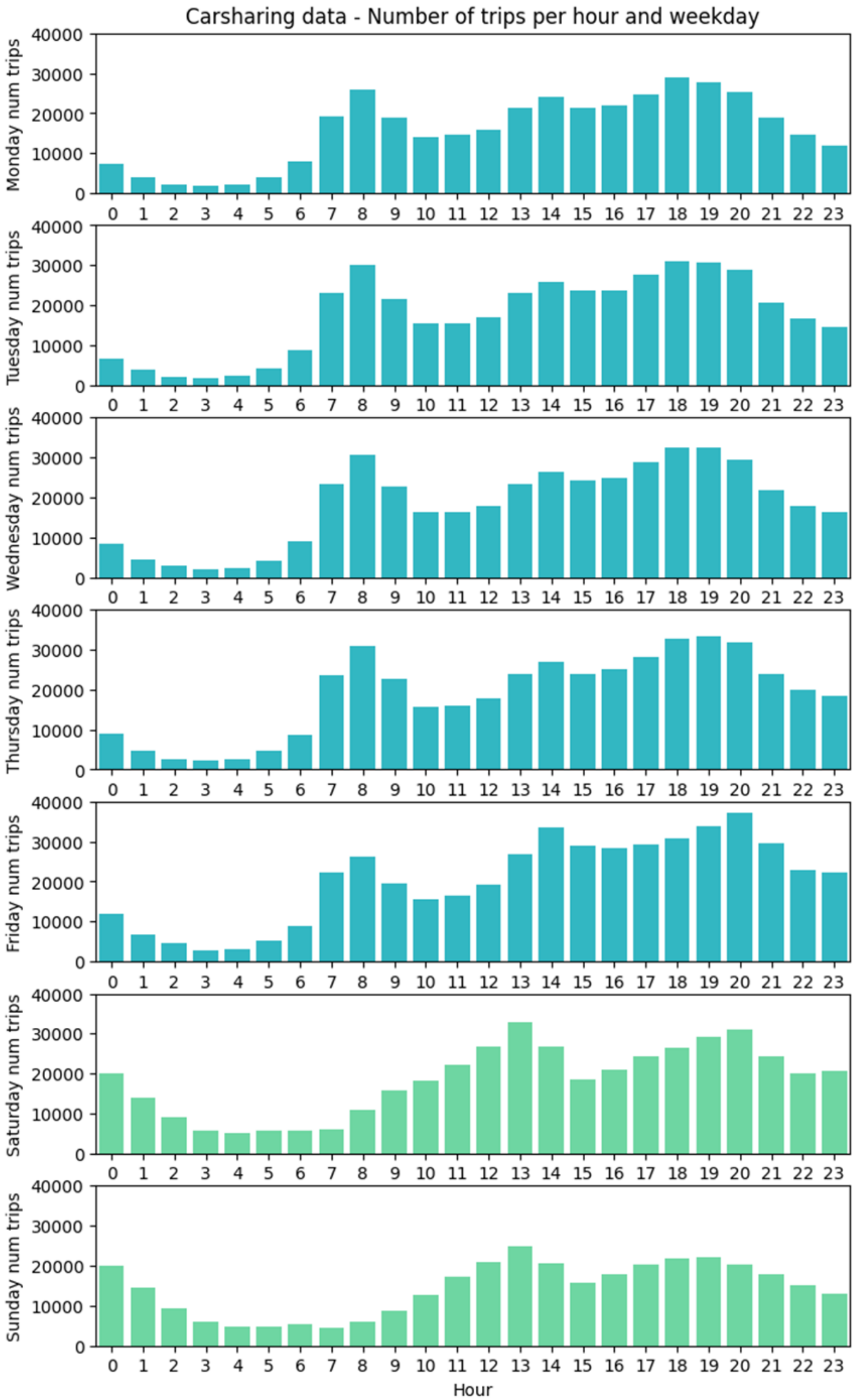

Figure 9 Carsharing trip volume by weekday and hour period

When adding categorising carsharing trips by distance, the resulting distribution peaks at around 3 km (Figure 10), which is consistent with the nature of carsharing trips and the areas of operation of these services. A significant volume of trips is grouped in trip distances close to 0. These probably correspond to trips that were not made, which suggest a need for a potential filter to correctly characterise the actual demand.

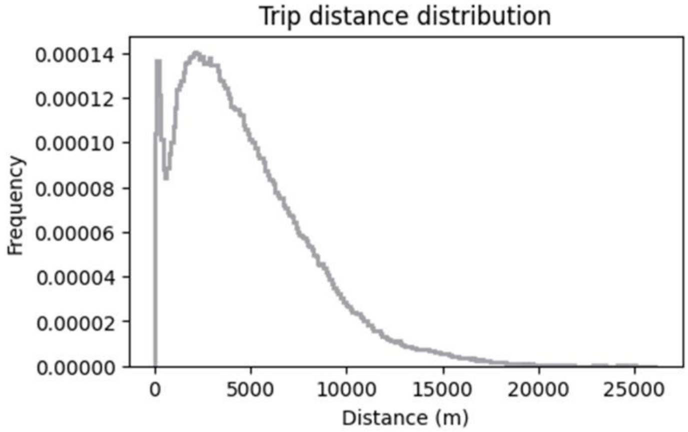

Figure 10 Carsharing trip distance distribution

Finally, Figure 11 focuses on the start location of each trip from the carsharing data. These have been plotted as a heatmap. The information is consistent with the population density and the service areas of operation.

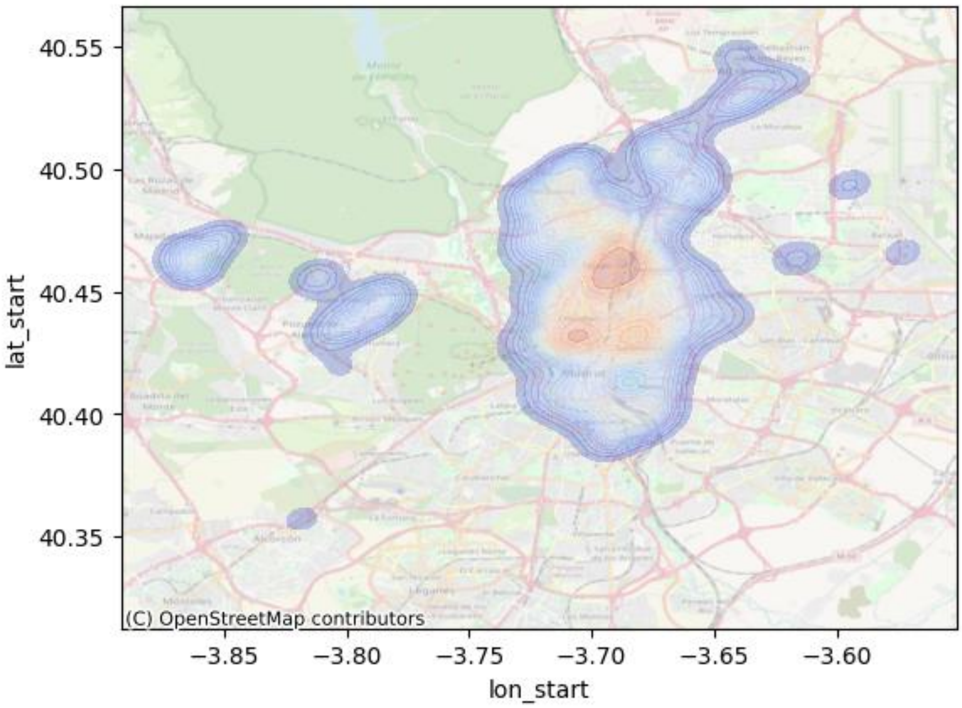

Figure 11 Carsharing trip origin location heatmap

3.4.3.2 Optimization model for dynamic delivery planning

This point aims to describe the design of an optimization model for the dynamic planning of last-mile logistics in combination with DRT. The main content of this subsection is dedicated to the descriptions of the mathematical models that have been used in the design and implementation of the Deusto dynamic last-mile logistics planner, therefore we are going to define the main concepts around last-mile logistics optimization, which we have considered relevant in the context of the project.

The solution model for last-mile transport optimization problems is considered a Rich Vehicle Routing Problem (RVRP) since it is a real-world problem and includes optimization criteria, constraints, and preferences. It is also a model that incorporates realistic optimization functions with different objectives, uncertainty in some components, dynamism, and a wide variety of real-life constraints related to time, distance, and the use of heterogeneous fleets.

The RVRP model is defined as a graph $G = V, E$, where V are the set of n nodes representing the customers and E is the set of arcs. The vehicle fleet can be modeled as heterogeneous (i.e., bikes, scooters, motorcycles, cars, trucks, etc.), defined as K_f, where each vehicle will have a capacity Q_f and will be located in a specific place. The VRP model and constraints are presented below, considering vehicle capacities, time windows and pickups-deliveries.

$$Min \sum_{(i,j)\in I} d_{ij}x_{ij} \qquad x_{ij} \in \{0,1\} \qquad \forall_{i,j} \in I \tag{14}$$

Subject to:

$$\sum_{i\in I} \sum_{t\in T} Y_{it} = 1 \qquad \forall_i \in I \tag{15}$$

$$\sum_{t\in T} \sum_{i\in I} P_i \sum_{i,j\in I} x_{i,j} \leq Q_{max} \tag{26}$$

$$\sum_{i\in I} x_{ijk} - \sum_{j\in I} x_{jik} = 0 \qquad \forall_{ij} \in I \tag{17}$$

Equation (14) refers to the objective function of the problem, whose purpose is to minimize the transportation cost, which can be a function of travel time or total distance travelled. Equation (15) is a constraint that aims to ensure that an order is served by only one vehicle. Equation (26) refers to the constraint that ensures that vehicles do not exceed their maximum capacity.

The notation used for the formulation of the VRP is:

- i, I: the index and set customers,
- $d_{i,j}$: distance (or travel time) between customers i and j,
- T: set of vehicles.

Starting from the classical VRP model, we will add new components to define a model for iterative and integrated planning from the perspective of its application to last-mile logistics and according to the objectives of the project.

These are mainly very complex problems where a large variety of constraints must be considered, e.g. time windows constraint, capacity constraint, where dynamism and uncertainty are present, and where more than one objective must be optimized simultaneously. The following points will define the models of the different components that will be integrated into our proposal, improving the existing optimization module according to the functional requirements and the defined use cases for the CONDUCTOR project.

The design of the new models developed in Task 3.4 will allow the optimization tool to work in an integrated way, combining the transportation of people with last-mile order deliveries. This will be based on three very important optimization paradigms. Firstly, iterative and dynamic optimization, which will allow us to consider the impact of the generated freight delivery routes in the general mobility and/or the current traffic conditions that may modify the initial planning of routes, such as vehicle breakdowns, traffic collapse in cities at peak times, etc. Secondly, multi-objective optimization, which will allow us to consider several objectives or performance indicators that can be optimized simultaneously, such as distance, cost, time, emissions, waiting times, etc. Finally, we will include robust optimization, which will allow us to introduce uncertainty in some elements of the model (travel times and service times for people), and to adjust the solutions to possible changing and uncertain conditions.

3.4.3.2.1 Demand and Time Dependence

Customer demand refers to a customer's order, that must be met by a vehicle, which knows in advance the location of the customer. Autonomous demand-responsive transportation will be used to provide this service to the customers. For this use case, the optimized DRT service also gives service to freight deliveries when the demand of passengers for DRT is low. Thus, passengers and freight could book a slot in the service.

The route optimization system that Deusto will develop for CONDUCTOR allows the definition of both pick-up and drop-off time windows for both passengers and goods. This allows modelling reservation-based vehicle-sharing systems and/or ensuring quality of service in last-mile logistics. The model will include information on demand (weight, volume), pickup or delivery time windows, and personalized preferences of the recipients in terms of pickup and delivery time windows.

$$tw_{start_i} \leq s_{t_i} \leq tw_{end_i} - s''_{t_i} \tag{18}$$

$$\sum_{i=0}^{I} [t_{(i,i+1),j} + w_{(i,j)} + s_{i,j}] \leq t_{max} \tag{193}$$

$$x_{ij}^k (y_i^k + g_i + t_{ij}(y_i^k + g_i)) \leq y_j^k \tag{20}$$

- tw_{start_i}: start of the time window for the availability of customer i
- tw_{end_i}: end of time window for the availability of customer i
- s_{t_i}: service time of the customer
- y_i^k: service start time for customer i served by vehicle k
- g_i: service time in customer i

Equation (18) is the constraint that aims to ensure that each customer's order is picked-up or delivered within the established time frame, i.e., within the time window of pickup or delivery. Equation (193) indicates the maximum time constraint of the route, where all vehicles must complete the route without exceeding a set maximum time. Equation **Error! Reference source not found.** refers to the fact that the service start time must allow for travel time between customers.

3.4.3.2.2 Restrictions and Dynamism

Constraints in vehicle routing models are a key element for the applicability of the models, and some of them are operationally related directly to the vehicle fleet, vehicle capacities, driver regulations, and time windows for deliveries or order pickups, among others. Managing last-mile logistics deliveries in urban areas is a very complex process, there are areas in cities where only pedestrians can circulate, and there are regulations on driving hours or access restrictions to certain types of vehicles in some areas (low emission zones, there is a maximum speed limit that can slow down deliveries, etc.

In last-mile logistics in cities, there is a strong dependence on the conditions and infrastructure of each locality (e.g., loading and unloading spaces and narrow streets). Driving constraints in urban areas must be considered when generating routes for delivery drivers, and traffic congestion at certain times can cause delays in deliveries to customers, which can lead to high transportation costs. The model will develop mechanisms to dynamically adjust the routes according to events and/or road or traffic conditions. To do so, the solution will make use of the tools developed for the CAVs routing and the communication services deployed with the centralized TMC. The characteristics that the model must meet to include driving restrictions are described below.

$$tw^s \leq tw_{end_i} - tw_{start_i} \leq tw^e \tag{21}$$

$$\sum_{k \in K} \sum_{i,j \in I} \sigma \, y_{i,j}^k \quad \sigma \in \{0,1\} \tag{22}$$

- tw^s: is the initial time window of a location with temporary access restrictions throughout the day, and
- tw^e: is the ending time window of a location with temporary access restrictions throughout the day.

Equation () is the time window constraint that must be met by orders that are in a location with access restrictions at certain times of the day. Equation () refers to the fact that certain vehicles will have limited access to delivery locations considering defined driving restrictions in urban areas.

3.4.3.2.3 Multi-objective

In the models of vehicle routing problems, the main objective is to minimize the cost of the solution, either in distance or in time, although in real problems they are multi-objective in nature. In a problem like VRP the objective function can be diverse, for example: minimizing the total distance travelled, the total time required, the total cost of the route, the size of the fleet, and maximizing the quality of the services and the profit obtained. In this sense, it is often very complex to reach a balance when multiple objectives are identified, as some may conflict.

In many real-life problems, such as food delivery, objectives like customer satisfaction and on-time delivery of orders are often more important than minimizing the distance travelled. To this end, a family of multi-objective VRPs (MOVRPS) was created, which will allow us to model real-life problems and extend the practical applications of this problem. For MOVRPs, a global optimization function can be defined that will have one or more objectives. These objectives, as already mentioned, are sometimes conflicting in nature, i.e., there are some trade-offs between them. The MOVRP can be stated as:

$$MOVRP = \begin{cases} max/min \; F(x) = (f_1(x), f_2(x), f_3(x), \ldots, f_n(x)) \\ s.t. \, x \in D \end{cases}$$

There are different objectives used in the MOVRP, among them is the objective related to the routes, which can be expressed in terms of distance or total travel time, and the number of customers visited. In addition, the objectives related to the resources available in the problem are known vehicles and available personnel; this objective is very important both economically and environmentally. For example, minimizing the number of vehicles used requires less investment costs and fewer emissions of polluting gases. Another objective could be related to time window constraints, since the violation of time windows can be minimized, with direct association to maximizing customer satisfaction.

To deal with the simultaneous optimization of different objectives that may conflict, we will use the weighted sum approach in our model. In the weighted sum method, the objective is to associate to each objective function a weight coefficient, which will indicate the preference or relevance of each objective, and to minimize the weighted sum of the objective functions. An example of our objective function considering the weighted sum of its components is shown below:

$$\text{Optimized KPIs} = \mathrm{w}_1 \cdot \text{distance} + \mathrm{w}_2 \cdot \text{time} + \mathrm{w}_3 \cdot \text{emisions} + \ldots + \mathrm{w}_\mathrm{n} \cdot \mathrm{KPI}_\mathrm{n}$$

3.4.3.3 FleetPy model description

This section details the main optimization model used by FleetPy for fleet management. It also describes the optimization approach planned to be developed for the integration of logistics into DRT services. The combined services will be simulated for the city of Madrid (Use Case 3).

The overall fleet management problem in DRT services falls under the category of SDVRP. FleetPy uses a dynamic simulation environment, where the ride requests are revealed over time. It uses two types of control algorithms for assigning vehicles to requests. The first type is quick response algorithms that respond to the requests as soon as they are revealed to the system. The second type accumulates the requests for a brief period and formulates an optimization problem for assigning vehicles to ride requests. The latter category is known as batch optimization, which is the focus of this section.

FleetPy represents the street network as a directed graph $G_{op} = (N_{op}, E_{op})$ with nodes N_{op} and edges E_{op}. Each edge $e \in E_{op}$ is associated with a distance d_e and a travel time $\tau_e(t)$. Since in CONDUCTOR, FleetPy is coupled with a microsimulation model offered by Aimsun Next, $\tau_e(t)$ will be estimated from the information collected from the Aimsun Next simulation, as described in deliverable D2.1 (Specification and initial version of the adapted traffic and fleet management models).

In each time step, FleetPy conducts four major steps:

1. Boarding and alighting of passengers as well as pick up or drop off events of freight requests are registered by the fleet operator.
2. New DRT customers enter the simulation and request a trip i at the time t_i by providing origin $o_i \in N_{op}$ and destination $d_i \in N_{op}$.
3. The operator evaluates whether it can serve the request within the given time constraints. If so, an expected pick-up time t_i^{pu} and drop-off time t_i^{do} is provided.
4. Operators accommodate a subset of freight requests into vehicle schedules
5. The operator assigns new/updated schedules to its vehicles.

In order to assign customers to vehicles, FleetPy first builds a pool of schedules. A schedule is defined as a series of stops at network nodes N_{op} where boarding and alighting processes of vehicles are conducted. In between these stops, vehicles are travelling on the fastest route in the network

G_{op}. There are multiple possible permutations of stops as soon as more than one passenger is assigned to a vehicle $v \in V$, which are further increased when freight requests are also considered. The k-th possible permutation of stops for the schedule $\psi_k(v; R_\psi, P_\psi)$ serving all passengers and freight requests in the set R_ψ and P_ψ, respectively, is considered feasible if all the following conditions are satisfied:

1. the drop-off stop succeeds the pick-up stop for each customer.
2. the number of on-board customers never exceeds the vehicle capacity (c_v).
3. each customer is (supposed to be) picked up before a maximum waiting time w_{max} elapsed.
4. if the operator offers a pooling service, the maximum additional travel time must not exceed a detour factor δ_{max} compared to a direct trip.

As described in deliverable D2.1 (Specification and initial version of the adapted traffic and fleet management models), FleetPy considers three levels of logistic integration: status quo (freight and passengers served by separate fleet), moderate (both served by same fleet, however, no parcel can be collected or delivered in between a passenger trip) and full (a freight request can also be collected or delivered in-between passenger trips). For a moderate integration to be considered, the optimization problem additionally uses the following constraint:

5. while passengers are in the vehicle, no stop is allowed where only parcels are picked up or dropped off.

Schedules are rated by an objective function $\phi(\psi_k(v; R_\psi, P_\psi))$. The goal of the fleet operator is to assign schedules minimizing the aggregated objective function for all its vehicles. $\phi(\psi_k(v; R_\psi, P_\psi))$ can be modelled in multiple ways, for example, currently FleetPy models the objective function as follows:

$$\phi(\psi_k(v; R_\psi, P_\psi)) = d(\psi_k(v; R_\psi, P_\psi) - P\,(|R_\psi| + |P_\psi|) \qquad (23)$$

where $d(\psi_k(v; R_\psi, P_\psi)$ refers to the distance to drive to complete the schedule. P is a large assignment reward to prioritize serving customers and parcels over minimizing the driven distance. The high-level simulation flow of the whole process is given in Figure 13.

To solve the above optimization problem for combined logistic and DRT service, FleetPy currently uses three heuristic approaches to build set of schedules that include freight requests. The fundamental concept of these heuristics is to only insert freight requests into vehicle schedules if the detour to pick up or drop off a freight request is small. The details and performance analysis of the heuristics is provided in (Fehn et al., 2023).

Within CONDUCTOR, TUM will further improve these solution strategies. The following summarizes the main improvements planned:

- Currently, the freight requests are not given any priority when the vehicle schedules are formed; rather, the freight requests are only served if the DRT happen to pass near the freight request locations while serving the DRT passengers. Therefore, a priority mechanism is set within the whole solution methodology for the freight requests that will also allow explicit trips for just serving the freight requests. Thus, a new objective function $\phi(\psi_k(v; R_\psi, P_\psi))$ will be formulated that allows this.
- TUM will also study if it's possible to provide certain time-window guarantee for freight deliveries. This replicates a similar strategy implemented by current freight services where the delivery of freight requests is given a rough delivery time-window, ranging in hours. This significantly raises the problem complexity, as this also includes forecasting which freight requests can be clustered in a way that the DRT vehicles are available in the neighbourhood to pick up and deliver the freight.

- Due to integration with the microsimulation model (Aimsun Next), the travel times between locations in the city are not static and can change after the assignment of vehicle schedules. Thus, it will also be studied how much these changing travel times can affect the performance of the developed strategies. Additionally, it will be investigated if vehicular routes that improve the traffic situation within the city can be actively taken.

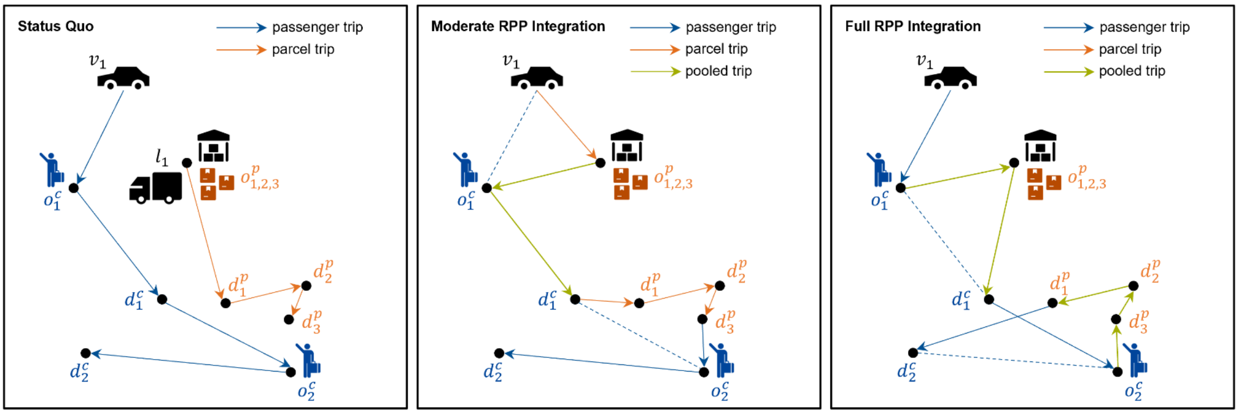

Figure 12 Integration levels of freight requests into DRT

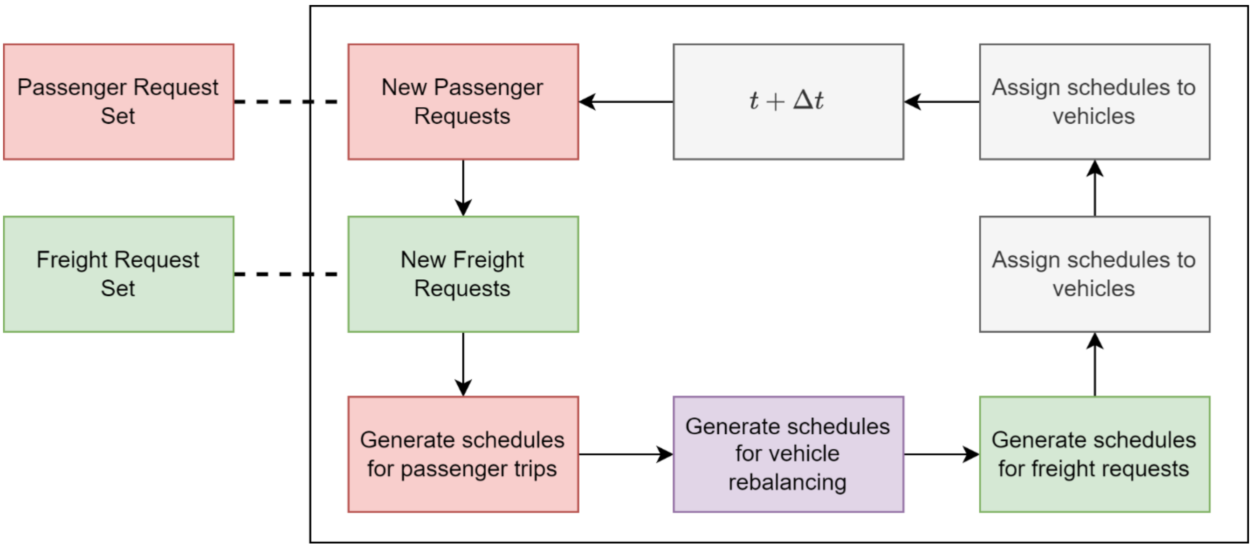

Figure 13 High level simulation flow of FleetPy integrated with freight requests

4 CONCLUSIONS

This deliverable provides an exhaustive overview about four topics namely traffic management with signal vehicle couple control, social routing, prediction models for DRT demand and optimization techniques for urban logistics. It also explains the ongoing effort under the CONDUCTOR project to further extend the solutions for those above-mentioned problems.

To address the problem of traffic management with CAVs we have developed a smart path distribution for the total demand of CAVs. For a specific OD pair, the smart optimization algorithm divides the total demand among the viable paths between the corresponding OD pair based on predefined KPIs like congestion, emission, travel delay and total energy consumption by the CAVs. This path distribution also supports de-centralized and hierarchical control for the distribution so that the transport system can have resilience.

With respect to the DRT demand, GoOpti's current transport fleet planning optimizes based on experiences and algorithms from passenger reservations. The main innovation will be in incorporating demand forecasting to enhance optimization algorithms for traffic routing and fleet operations. This forward-looking approach is set to significantly improve the adaptability of real-time demand-responsive transport services, ensuring GoOpti remains agile in meeting both present and future passenger needs.

Regarding the optimization of last-mile delivery, we are integrating the urban distribution of goods with DRT services. The solution aims to reduce the impact of delivery services in the city centres. For doing that we are adapting and improving already designed solution for efficient traffic management by using green vehicles and/or optimizing delivery routes. The results of this solution, adapted and improved to consider freight distribution, combined with the demand simulators and the use of CCAM pretend to improve the logistics meanwhile guaranteeing the quality of service for the passengers. Additionally, to model the combined operation of logistics and DRT, we are currently using heuristics to solve the combined optimization problem for fleet management. These are planned to be further improved. The main innovation in this regard is the inclusion of estimated delivery windows for the freight requests and realistic travel times based on Aimsun-FleetPy integration.
To further enhance the network load balancing process, we also have included the concepts of social routing and indifference bands into network design, which will enable us to improve network performance without triggering significant changes in travel behavior as long as the level of service for (groups of) users is not substantially degraded. Within the CONDUCTOR project, we use these concepts in developing various system optimum models while suggesting socially desired routes to a portion of public transport riders, as well as real-time optimization of signal settings with embedded conditional signal priority to a group of road users to improve the network performance. Meanwhile, a minimum acceptable level of service and safety margins must always be ensured.

5 REFERENCES

1. Abdirad, M., Krishnan, K., & Gupta, D. (2022). Three-stage algorithms for the large-scale dynamic vehicle routing problem with industry 4.0 approach. *Journal of Management Analytics*, *9*(3), 313–329. https://doi.org/10.1080/23270012.2022.2113161
2. Adewumi, A. O., & Adeleke, O. J. (2018). A survey of recent advances in vehicle routing problems. *International Journal of System Assurance Engineering and Management*, *9*(1), 155–172. https://doi.org/10.1007/s13198-016-0493-4
3. Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. *Proceedings of the National Academy of Sciences*, *114*(3), 462–467. https://doi.org/10.1073/pnas.1611675114
4. Arslan, A. M., Agatz, N., Kroon, L., & Zuidwijk, R. (2019). Crowdsourced Delivery—A Dynamic Pickup and Delivery Problem with Ad Hoc Drivers. *Transportation Science*, *53*(1), 222–235. https://doi.org/10.1287/trsc.2017.0803
5. Ashraf, M. T., Dey, K., & Mishra, S. (2023). Identification of high-risk roadway segments for wrong-way driving crash using rare event modeling and data augmentation techniques. *Accident Analysis & Prevention*, *181*, 106933.
6. Bai, S., Kolter, J. Z., & Koltun, V. (2018). An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. *arXiv Preprint arXiv:1803.01271*.
7. Baldacci, R., Mingozzi, A., & Roberti, R. (2012). Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints. *European Journal of Operational Research*, *218*(1), 1–6. https://doi.org/10.1016/j.ejor.2011.07.037
8. Barker, J. (2020). Machine learning in M4: What makes a good unstructured model? *International Journal of Forecasting*, *36*(1), 150–155.
9. Beirigo, B. A., Schulte, F., & Negenborn, R. R. (2018). Integrating People and Freight Transportation Using Shared Autonomous Vehicles with Compartments. *IFAC-PapersOnLine*, *51*(9), 392–397. https://doi.org/10.1016/j.ifacol.2018.07.064
10. Berhan, E., Beshah, B., Kitaw, D., & Abraham, A. (2014). Stochastic Vehicle Routing Problem: A Literature Survey. *Journal of Information & Knowledge Management*, *13*(03), 1450022. https://doi.org/10.1142/S0219649214500221
11. Braekers, K., Ramaekers, K., & Van Nieuwenhuyse, I. (2016). The vehicle routing problem: State of the art classification and review. *Computers & Industrial Engineering*, *99*, 300–313. https://doi.org/10.1016/j.cie.2015.12.007
12. Caceres-Cruz, J., Arias, P., Guimarans, D., Riera, D., & Juan, A. A. (2015). Rich Vehicle Routing Problem: Survey. *ACM Computing Surveys*, *47*(2), 1–28. https://doi.org/10.1145/2666003
13. Dai, R., Ding, C., Wu, X., Yu, B., & Lu, G. (2023). Coupling Control of Traffic Signal and Entry Lane at Isolated Intersections Under the Mixed-Autonomy Traffic Environment. *IEEE Transactions on Intelligent Transportation Systems*.
14. Debarshi, S., Sundaram, S., & Sundararajan, N. (2022). Robust EMRAN-aided coupled controller for autonomous vehicles. *Engineering Applications of Artificial Intelligence*, *110*, 104717.
15. Dong, X., Lei, T., Jin, S., & Hou, Z. (2018). Short-term traffic flow prediction based on XGBoost. *2018 IEEE 7th Data Driven Control and Learning Systems Conference (DDCLS)*, 854–859.

16. Du, Y., ShangGuan, W., & Chai, L. (2021). A Coupled Vehicle-Signal Control Method at Signalized Intersections in Mixed Traffic Environment. *IEEE Transactions on Vehicular Technology*, *70*(3), 2089–2100. https://doi.org/10.1109/TVT.2021.3056457

17. Elshaer, R., & Awad, H. (2020). A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants. *Computers & Industrial Engineering*, *140*, 106242. https://doi.org/10.1016/j.cie.2019.106242

18. Engelhardt, R., Dandl, F., Bilali, A., & Bogenberger, K. (2019). Quantifying the Benefits of Autonomous On-Demand Ride-Pooling: A Simulation Study for Munich, Germany. *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, 2992–2997. https://doi.org/10.1109/ITSC.2019.8916955

19. Fehn, F., Engelhardt, R., & Bogenberger, K. (2021). Ride-Parcel-Pooling—Assessment of the Potential in Combining On-Demand Mobility and City Logistics. *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, 3366–3372. https://doi.org/10.1109/ITSC48978.2021.9564630

20. Fehn, F., Engelhardt, R., Dandl, F., Bogenberger, K., & Busch, F. (2023). Integrating parcel deliveries into a ride-pooling service—An agent-based simulation study. *Transportation Research Part A: Policy and Practice*, *169*, 103580. https://doi.org/10.1016/j.tra.2022.103580

21. Gass, S. I., & Fu, M. C. (Eds.). (2013). *Traveling Salesman Problem*. Springer US.

22. Gers, F. A., Eck, D., & Schmidhuber, J. (2002). Applying LSTM to time series predictable through time-window approaches. In *Neural Nets WIRN Vietri-01* (pp. 193–200). Springer.

23. Ghilas, V., Demir, E., & Van Woensel, T. (2016). An adaptive large neighborhood search heuristic for the Pickup and Delivery Problem with Time Windows and Scheduled Lines. *Computers and Operations Research*, *72*, 12–30.

24. Ghoul, T., & Sayed, T. (2021). Real-time signal-vehicle coupled control: An application of connected vehicle data to improve intersection safety. *Accident Analysis & Prevention*, *162*, 106389.

25. Goel, R. K., & Bansal, S. R. (2019). Hybrid algorithms for rich vehicle routing problems: A survey. *Smart Delivery Systems: Solving Complex Vehicle Routing Problems*, 157–184.

26. Golden, B., Raghavan, S., & Wasil, E. (Eds.). (2008). *The Vehicle Routing Problem: Latest Advances and New Challenges* (Vol. 43). Springer US. https://doi.org/10.1007/978-0-387-77778-8

27. Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L.-M. (2016). An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. *European Journal of Operational Research*, *254*(1), 80–91. https://doi.org/10.1016/j.ejor.2016.03.040

28. Guo, F., Polak, J. W., Krishnan, R., & others. (2018). Predictor fusion for short-term traffic forecasting. *Transportation Research Part C: Emerging Technologies*, *92*, 90–100.

29. Guo, Q., & Ban, X. J. (2023). A multi-scale control framework for urban traffic control with connected and automated vehicles. *Transportation Research Part B: Methodological*, *175*, 102787.

30. Huang, W., Song, G., Hong, H., & Xie, K. (2014). Deep architecture for traffic flow prediction: Deep belief networks with multitask learning. *IEEE Transactions on Intelligent Transportation Systems*, *15*(5), 2191–2201.

31. Jin, F., & Sun, S. (2008). Neural network multitask learning for traffic flow forecasting. *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, 1897–1901.

32. Jozefowiez, N., Semet, F., & Talbi, E.-G. (2008). Multi-objective vehicle routing problems. *European Journal of Operational Research*, *189*(2), 293–309. https://doi.org/10.1016/j.ejor.2007.05.055

33. Kumar, M., & Thenmozhi, M. (2006). Forecasting stock index movement: A comparison of support vector machines and random forest. *Indian Institute of Capital Markets 9th Capital Markets Conference Paper*.

34. Li, B., Krushinsky, D., Reijers, H. A., & Van Woensel, T. (2014). The Share-a-Ride Problem: People and parcels sharing taxis. *European Journal of Operational Research*, *238*(1), 31–40. https://doi.org/10.1016/j.ejor.2014.03.003

35. Li, B., Krushinsky, D., Van Woensel, T., & Reijers, H. A. (2016). An adaptive large neighborhood search heuristic for the share-a-ride problem. *Computers & Operations Research*, *66*, 170–180. https://doi.org/10.1016/j.cor.2015.08.008

36. Li, G., Knoop, V. L., & van Lint, H. (2021). Multistep traffic forecasting by dynamic graph convolution: Interpretations of real-time spatial correlations. *Transportation Research Part C: Emerging Technologies*, *128*, 103185.

37. Lim, B., Arik, S. O., Loeff, N., & Pfister, T. (2019). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *arXiv Preprint arXiv:1912.09363*.

38. Lim, B., & Zohren, S. (2021). Time-series forecasting with deep learning: A survey. *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200209.

39. Louati, A., Louati, H., Nusir, M., & Hardjono, B. (2020). Multi-agent deep neural networks coupled with LQF-MWM algorithm for traffic control and emergency vehicles guidance. *Journal of Ambient Intelligence and Humanized Computing*, *11*, 5611–5627.

40. Luk, K. C., Ball, J. E., & Sharma, A. (2000). A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting. *Journal of Hydrology*, *227*(1–4), 56–65.

41. Ma, S., Zheng, Y., & Wolfson, O. (2015). Real-Time City-Scale Taxi Ridesharing. *IEEE Transactions on Knowledge and Data Engineering*, *27*(7), 1782–1795. https://doi.org/10.1109/TKDE.2014.2334313

42. Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). The M4 Competition: Results, findings, conclusion and way forward. *International Journal of Forecasting*, *34*(4), 802–808.

43. Manchella, K., Umrawal, A. K., & Aggarwal, V. (2021). FlexPool: A Distributed Model-Free Deep Reinforcement Learning Algorithm for Joint Passengers and Goods Transportation. *IEEE Transactions on Intelligent Transportation Systems*, *22*(4), 2035–2047. https://doi.org/10.1109/TITS.2020.3048361

44. Medsker, L. R., & Jain, L. (2001). Recurrent neural networks. *Design and Applications*, *5*, 64–67.

45. Mei, J., He, D., Harley, R., Habetler, T., & Qu, G. (2014). A random forest method for real-time price forecasting in New York electricity market. *2014 IEEE PES General Meeting| Conference & Exposition*, 1–5.

46. Mor, A., & Speranza, M. G. (2020). Vehicle routing problems over time: A survey. *4OR*, *18*(2), 129–149. https://doi.org/10.1007/s10288-020-00433-2

47. Mourad, A., Puchinger, J., & Chu, C. (2019). A survey of models and algorithms for optimizing shared mobility. *Transportation Research Part B: Methodological*, *123*, 323–346. https://doi.org/10.1016/j.trb.2019.02.003

48. Narayanan, S., Chaniotakis, E., & Antoniou, C. (2020). Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C*, *111*, 255–293.

49. Okulewicz, M., & Mańdziuk, J. (2019). A metaheuristic approach to solve Dynamic Vehicle Routing Problem in continuous search space. *Swarm and Evolutionary Computation*, *48*, 44–61. https://doi.org/10.1016/j.swevo.2019.03.008

50. Oreshkin, B. N., Carpov, D., Chapados, N., & Bengio, Y. (2019). N-BEATS: Neural basis expansion analysis for interpretable time series forecasting. *arXiv Preprint arXiv:1905.10437*.

51. O'Shea, K., & Nash, R. (2015). An introduction to convolutional neural networks. *arXiv Preprint arXiv:1511.08458*.

52. Pham, A.-D., Kuestenmacher, A., & Ploeger, P. G. (2023). TSEM: Temporally-Weighted Spatiotemporal Explainable Neural Network for Multivariate Time Series. In K. Arai (Ed.), *Advances in Information and Communication* (Vol. 652, pp. 183–204). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-28073-3_13

53. Pillac, V., Gendreau, M., Guéret, C., & Medaglia, A. L. (2013). A review of dynamic vehicle routing problems. *European Journal of Operational Research*, *225*(1), 1–11. https://doi.org/10.1016/j.ejor.2012.08.015

54. Potvin, M., & Gendreau, J.-Y. (Eds.). (2019). *Handbook of Metaheuristics* (Vol. 272). Springer International Publishing.

55. Psaraftis, H. N., Wen, M., & Kontovas, C. A. (2016). Dynamic vehicle routing problems: Three decades and counting. *Networks*, *67*(1), 3–31. https://doi.org/10.1002/net.21628

56. Qi, D., & Majda, A. J. (2020). Using machine learning to predict extreme events in complex systems. *Proceedings of the National Academy of Sciences*, *117*(1), 52–59. https://doi.org/10.1073/pnas.1917285117

57. Raidl, G. R. (2006). A unified view on hybrid metaheuristics. *Lecture Notes in Computer Science*, *4030 LNCS*, 1–12.

58. Ruch, C., Lu, C., Sieber, L., & Frazzoli, E. (2021). Quantifying the Efficiency of Ride Sharing. *IEEE Transactions on Intelligent Transportation Systems*, *22*(9), 5811–5816. https://doi.org/10.1109/TITS.2020.2990202

59. Salinas, D., Flunkert, V., Gasthaus, J., & Januschowski, T. (2020). DeepAR: Probabilistic forecasting with autoregressive recurrent networks. *International Journal of Forecasting*, *36*(3), 1181–1191.

60. Santi, P., Resta, G., Szell, M., Sobolevsky, S., Strogatz, S., & Ratti, C. (2014). Quantifying the benefits of vehicle pooling with shareability networks. *Proceedings of the National Academy of Sciences*, *111*(37), 13290–13294. https://doi.org/10.1073/pnas.1403657111

61. Spiliotis, E., Makridakis, S., Semenoglou, A.-A., & Assimakopoulos, V. (2020). Comparison of statistical and machine learning methods for daily SKU demand forecasting. *Operational Research*, 1–25.

62. Wang, X., Yuan, Y., Tong, L., Yuan, C., Shen, B., & Long, T. (2023). Energy Management Strategy for Diesel–Electric Hybrid Ship Considering Sailing Route Division Based on DDPG. *IEEE Transactions on Transportation Electrification*, 1–1. https://doi.org/10.1109/TTE.2023.3263328

63. Wen, H., Lin, Y., Xia, Y., Wan, H., Wen, Q., Zimmermann, R., & Liang, Y. (2023). *DiffSTG: Probabilistic Spatio-Temporal Graph Forecasting with Denoising Diffusion Models* (arXiv:2301.13629). arXiv. http://arxiv.org/abs/2301.13629

64. Xie, B., Deng, Y., Shao, Z., Liu, H., Xu, Q., & Li, Y. (2023). *Event Voxel Set Transformer for Spatiotemporal Representation Learning on Event Streams* (arXiv:2303.03856). arXiv. http://arxiv.org/abs/2303.03856

65. Yang, J., Liu, B., Zhang, T., Hong, J., & Zhang, H. (2023). Multi-parameter-controlled mechatronics-electro-hydraulic power coupling electric vehicle based on active energy regulation. *Energy*, *263*, 125877.

66. Yun, S., Namkoong, S., Shin, S., Rho, J., & Choi, J. (1996). Application of a Recurrent Neural Network to Traffic Volume Forecasting. *Intelligent Transportation: Realizing the Future. Abstracts of the Third World Congress on Intelligent Transport SystemsITS America*.

67. Zhang, H., Zou, Y., Yang, X., & Yang, H. (2022). A Temporal Fusion Transformer for Short-term Freeway Traffic Speed Multistep Prediction. *Neurocomputing*.

68. Zhang, J., Zheng, Y., & Qi, D. (2017). Deep spatio-temporal residual networks for citywide crowd flows prediction. *Thirty-First AAAI Conference on Artificial Intelligence*.

69. Zhao, Z., Chen, W., Wu, X., Chen, P. C., & Liu, J. (2017). LSTM network: A deep learning approach for short-term traffic forecast. *IET Intelligent Transport Systems*, *11*(2), 68–75.

A. ABBREVIATIONS AND DEFINITIONS

Term	Definition
ARIMA	Auto-Regressive Integrated Moving Average
ATSC	Adaptive Traffic Signal Controllers
CAV	Connected autonomous vehicle
CCAM	Connected, Cooperative and Automated Mobility
CNN	Convolutional neural networks
CVSC	Coupled Vehicle-Signal Control
DRT	Demand-Responsive Transport
DSRC	Dedicated Short-Range Communication
DVRP	Dynamic vehicle routing problems
EMRAN	Extended Minimal Resource Allocating Network
FLO-EMS	Fuzzy logic optimization energy management method
GLOSA	Green Light Optimal Speed Advisory
HDV	Human-Driven Vehicles
LNS	Large neighbourhood search
LQF-MWM	Longest Queue First Maximal Weight Matching algorithm
LSTM	Long short-term memory
MEH-PCEV	Mechatronics-electro-hydraulic power coupling electric vehicle
ML	Machine Learning
MND	Mobile Network Data
MPC	Model Predictive Control
N-BEATS	Neural basis expansion analysis for time series
NP-hard	Non-deterministic polynomial-time hardness
OD	Origin Destination
OR	Operational research
PT	Public Transport
RBF	Radial basis function
RFE	Recursive Feature Elimination
RNN	Recurrent neural network
SARIMA	Seasonal Auto-Regressive Integrated Moving Average
SVCC	Signal Vehicle Couple Control
Term	Definition
TFC	Total-Factor Control
TSCS	Traffic Signal Control Systems
TSP	Travelling Salesman Problem
UAV	Unmanned aerial vehicles
UC	Use case

Term	Definition
V2I	Vehicle-to-Infrastructure
VRP	Vehicle Routing Problem