TANGENT

Analysis of Current Approaches in Optimization of Transport Network Management

D5.1

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 955273

Deliverable administrative information

Deliverable number	D5.1
Deliverable title	Analysis of current approaches in optimization of transport network management
Dissemination level	Public
Submission deadline	31/05/2022
Version number	1.0
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Document approval	Not applicable

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Executive summary

One of the key objectives of the TANGENT project is to propose advanced techniques for modelling and simulation, optimization and control that can capture the dynamics of traffic and demand and adapt to evolving complex multimodal transport settings. In this complex environment, the optimization of traffic management and the multimodal transport network plays an important role since it allows users to have better door-to-door mobility and transport authorities to improve the management of the transport network.

This deliverable aims to analyze scientific literature related to current approaches to transport network management optimization within a multi-actor setting. Concretely, we focus our literature review on the three following problems because they play a relevant role in the management of mobility at a network level, where different actors and means of transport must be coordinated:

- **Signal Vehicle Couple Control with CAVs.** It aims to improve the traffic control performance by leveraging the exchange of information in real-time between signals and vehicles (connected vehicles and CAVs), and the simultaneous optimization of signals timing/phases and CAVs trajectories and/or routes, to enhance the performance of the whole traffic network.
- **Synchronization of shared and on-demand mobility with transit modes.** It is an area of vital importance because it can contribute to public transport's future position as the backbone of mobility in urban areas. Concretely, it can provide a solution to addressing the first/last mile problem of transit modes, especially in areas not densely populated and with infrequent public transport services since these modes can act as feeders or collectors of public transit.
- **Dynamic Congestion Pricing**. It is a variant of congestion pricing where prices vary dynamically in real-time as a function of current traffic conditions. This approach is opposed to flat pricing, which stays constant over time, and scheduled pricing, where tolls vary by time of day, day of the week or season following a predetermined schedule.

In the review of the literature, we analysed the optimization models and techniques commonly used in the scientific literature reviewed for the three categories of problems mentioned above. Here it is important to mention that the literature review focused only on papers that address those problems from a pure optimization perspective. In this analysis of the literature, we considered aspects such as the application scope, the optimization models (decision variable, constraints, objective function and modelling approach) and methods used, the experimental benchmark used and the comparison studies performed. From this literature review, the main research gaps identified for each problem were the following:

- **Signal Vehicle Couple Control with CAVs**
  - Most of the literature considered a single objective for the optimization purpose but inherently the SVCC problem is multi-objective in nature.
  - Most of the studies published so far are conducted under a 100% CAV scenario or a mixed traffic scenario with a high penetration rate of CAVs.
  - Only a few studies focus on the optimization of SVCC at the corridor or network level.
- **Synchronization of shared and on-demand mobility with transit modes**
  - Only a few papers addressed the synchronization of shared- and on-demand mobility with public transit in rural scenarios.
  - Lack of studies considering shared or on-demand services based on CAVs for their synchronization with public transport.
  - Most of the studies focus on synthetic data which can lead to biased conclusions.

- **Dynamic Congestion Pricing**
    - Most of the current DCP schemes are based on single-objective models.
    - Only a few papers address large-scale applications of DCP schemes because of their computational complexity.

Based on the literature review previously mentioned and on the priorities defined by the different case studies in Deliverable D1.1, in this document, we also provide a description and a justification of the particular optimization problems in transport network management in which we will focus on the upcoming tasks of TANGENT. Concretely, the chosen optimization problems are:

- **Coupled traffic signal and route planning optimization for CAVs**. Concretely, the objective is the coupled optimization (considering multiple objectives) of traffic signal control and CAVs schedules and routes at corridor level (at least) and under a mixed traffic scenario.
- **Optimization of integration DRT systems with public transit modes**. More specifically, the aim is the joint optimisation of the capacity (frequency and size of allocated vehicles) of public transport lines and the prioritisation of public transport at signalised intersections based on dynamic transit assignment models.
- **Synchronization of public transport and Traffic control**. In this case, the objective is the joint optimisation of the capacity (frequency and size of allocated vehicles) of public transport lines and the prioritisation of public transport at signalised intersections based on dynamic transit assignment models.
- **Optimization of Dynamic Congestion Pricing schemes**. Concretely, here we aim at the optimization of DCP schemes using a multi-objective and within-day approach making use of model-based optimization and parallel computing.

In this document, we also review literature related to **negotiation and arbitration models for transport network management**. Concretely, we focus on integrated decision-making, given that designing and operating urban transportation systems is a complex process that must consider various factors (e.g. economic, environmental, and socio-political), and that entails the involvement of various stakeholders with their own objectives and priorities. However, involving different stakeholders in the decision-making process has proven benefits for the multiple components that constitute the urban transport network. For this reason, in this deliverable, we discuss different consensus definitions, distinguishing between a “hard” and “soft” interpretation of consensus, and we examine ways to measure it. We also review traditional approaches to selecting the optimal solution when the stakeholders have different preferences focusing on Cost-Benefit Analysis methods, Multi-criteria Decision-making techniques and preference-based Evolutionary Algorithms. After that, we also discuss the state-of-the-art in decision-making approaches based on the principles of Agent-Based Modelling, focusing on Agent-Based Negotiations and Agent-Based Social Dynamics. Finally, considering all the review literature on this topic, we provide practical guidelines that delineate the development of a consensus-reaching mechanism, discussing its objective, scope, domain of application, stakeholders, data needs and modelling approach, and how they will be applied in the context of the TANGENT project.

Finally, we also overview software tools that can be used for the optimization of transport network management, which can be grouped into two categories, namely, machine learning-oriented (SMAC, Keras, TensorFlow, TensorFlow Model Optimization, Scikit-learn), and optimization-oriented (DEAP, PyMoo7 and Nevergrad).

Keywords

Transport Network Optimization, Traffic Management, Adaptative Traffic Control, CAVs, On-Demand Mobility, Transit Modes, Public Transport, Dynamic Pricing, Arbitration Models.

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List of abbreviations and acronyms

Acronym	Meaning
ABC	Artificial Bee Colony Algorithm
ABM	Actor Based Modelling
AHP	Analytic Hierarchy Problem
CAVs	Connected Autonomous Vehicles
CBA	Cost Benefit Analysis
DARP	Dial-a-Ride Problem
DCP	Dynamic Congestion Pricing
DEAHP	Data Envelopment Analysis
DRT	Demand Responsive Traffic
DTA	Dynamic Traffic Assignment
EC	Evolutionary Computation
EEA	Economic Effect Analysis
FIFO	First in First Out
GA	Genetic Algorithm
ITS	Intelligent Transportation Systems
LP	Linear programming
MAMCA	Multi Actor Multi Criteria Analysis
MAUT	Multi Attribute Utility Theory
MCDM	Multi-Criteria Decision Making
ML	Machine Learning
NLP	Natural language Processing
PSO	Particle Swarm Optimization
QCP	Quadratic Constrained Programming
QP	Quadratic Programming
SCBA	Social-Cost Benefit Analysis
SI	Swarm Intelligence
SVCC	Signal Vehicle Couple Control
TNM	Transport Network Management
TSC	Traffic Signal Control
TST	Traffic Signal Timing
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
WP	Work package
SyncOnDemand	Synchronization of on-demand and transit modes

1 Purpose of the deliverable

1.1 Attainment of the objectives and explanation of deviations

This deliverable is linked to Task 5.1 “Analysis of current approaches in Transport Network Optimization in a multi-actor setting” and therefore to the outcomes of this task that are. Firstly, to define a catalogue of the different techniques for transport network-optimization in a multi-actor setting (including the calibration of arbitration models), identifying their strengths and weaknesses. Secondly, to select and define the specific optimization problems to be addressed in TANGENT project (within the areas mentioned above). Thirdly, to define a set of guidelines for the development of calibration models. The objectives related to this deliverable have been achieved in full and as scheduled.

1.2 Intended audience

This deliverable is mainly intended for the scientific community, transport and mobility practitioners, policy makers, and postgraduate students in the areas of transportation and computer science.

1.3 Structure of the deliverable and links with other work packages/deliverables

This deliverable is directly related to other tasks within WP5 and consequently deliverables. More specifically, D5.1 will review and provide a complete view of current approaches to optimization of transport network management within a multi-actor setting. The literature review carried out on this deliverable will result in critical input for the Formulation and modelling of Transport Network optimization problems (Task 5.2), the design of optimization techniques for transport network optimization (Task 5.3), and the development of arbitration models (Task 5.4). Therefore, D5.1 is the starting point for the following deliverables: D5.2 Optimization models for transport network management, D5.3 Optimization techniques for transport network management, and D5.4 Calibration of arbitration models.

2 Introduction

Transport is a cornerstone for the movement of people, services and goods in the European Union. Specifically, this sector is a significant contributor to the European economy, representing more than 9% of the EU gross value added and accounting for approximately more than €600 billion in gross value. In this context of economic benefits, the mobility of passengers and the movement of goods on transport networks play an essential role in fulfilling the EU's energy and climate objectives related to transport. Specifically, transport management from a multimodal perspective is crucial for deploying innovative and sustainable means of transport at a network level.

On the other hand, the major changes that mobility is undergoing in recent years, with the arrival of emerging modes of transport (e.g. ride-hailing, car-sharing, bike-sharing, etc.), and which are expected in the coming years with the arrival of CAVs, may represent a window of opportunity to address the challenges mentioned above. However, they must be used in the right way, as public transport and active mobility must be at the heart of the mobility of the future, particularly in urban areas. For this reason, public authorities in charge of transport network management must orchestrate and coordinate both current and future transport modes. In this context, the following areas are of utmost importance: adaptive traffic control and CAVs, synchronization of on-demand and transit modes, dynamic congestion pricing and integrated decision-making.

In the case of adaptive traffic control and CAVs, the relevance is given by the great potential of CAVs to significantly improve traffic management (Skabardonis, 2020). In this sense, one of the main advances for coordinated traffic management that we can see in the future is the simultaneous optimization of vehicle operations and signal/timing phases to improve the performance of traffic flow at intersections. This is called Signal Vehicle Coupled Control. In a more specific way, it aims to improve the traffic control performance by leveraging the exchange of information in real-time between signals and vehicles (connected vehicles and CAVs), and the simultaneous optimization of signals timing/phases and CAVs trajectories and/or routes (Guo, Li, and (Jeff) Ban 2019), to enhance the performance of the whole traffic network.

Regarding the synchronization of on-demand and transit modes, it is also an area of vital importance because it can contribute to public transport's future position as the backbone of mobility in urban areas. Concretely, the literature shows that it can contribute to addressing the first/last mile problem of transit modes, especially in areas not densely populated and with infrequent public transport services (Charisis, Iliopoulou, and Kepaptsoglou 2018; Grahn, Qian, and Hendrickson 2021), since these modes can act as feeders or collectors of public transit modes.

Concerning the third area mentioned above, dynamic congestion pricing policies have gained high relevance in recent years because of their promising effects on reducing traffic congestion and transport emissions. The recent literature contributes to the reduction of traffic on specific roads, the maintenance of average speed, the promotion of carpooling and public transportation, the restriction of a particular type of vehicle, the restriction of traffic at specific times and on specific occasions, the generation of revenue, and the balance of cost between payer and payee (Lombardi et al., 2021).

As for the fourth area mentioned above, integrated decision-making, its importance comes from the fact that designing and operating urban transportation systems is a complex process that must consider various factors (e.g. economic, environmental, and socio-political). The heterogeneity of transport network components lies unavoidably outside the realms of responsibility of various stakeholders. As a result, it is common to find several private and public stakeholders involved in the design and management of urban transportation networks, each with their own objectives and priorities (Mardani et al., 2015). Involving different stakeholders in the decision-making process has proven benefits for the multiple components that constitute the urban transport network. In the planning of transport network systems and operations, addressing the stakeholder needs is recognized as a critical success factor, enabling the timely foresight of potential issues.

Having presented the main areas of interest that will be covered in this deliverable, this document aims to review and analyze current approaches to optimization of transport network management within a multi-actor setting. For this scope, we structure this document as follows. Section 3 reviews optimization problems within the categories of adaptative traffic control and CAVs, synchronization of on-demand with transit modes, and dynamic congestion pricing. Then, Section 4 introduces the optimization models and techniques commonly used in the state-of-the-art for the three categories of problems mentioned. Afterwards, and based on the literature review, Section 5 summarizes and justifies the particular optimization problems in transport network management on which the upcoming tasks of the WP5 of the TANGENT project will focus. Section 6 presents a review of negotiation and arbitration models for transport network management and also includes a set of guidelines for its development. Section 7 outlines software tools typically used in the fields of Machine Learning and Optimization that can be relevant tools to address the optimization problems identified in the previous sections. Finally, Section 8 presents the main conclusions of this deliverable.

3 Optimization problems in Transport Network Management

3.1 Adaptative traffic control and CAVs

3.1.1 Introduction

Investigations on autonomous driving have lasted for almost a century; for example, in 1925, Francis tested his radio-controlled driverless car in New York City's congested traffic («Houdina Radio Control», 2022). More than ever before, significant effort is being invested into the development of driverless vehicles. Modules with autonomous-driving capabilities are becoming increasingly common in passenger cars on the market. Fully autonomous vehicles are being tested in test cases and on highways all around the world.
To accommodate the rising traffic demands, urban traffic control (UTC) technologies have been regularly updated and reinvented (W. Li & Ban, 2019). Among the various novel traffic control approaches developed recently, connected and autonomous vehicles (CAVs) are seen to have significant potential (Mahmassani, 2016) Specially, cars that can communicate with other vehicles (vehicle-to-vehicle, V2V), infrastructure (vehicle-to-infrastructure, V2I), and other traffic participants such as pedestrians and bicyclists are typically referred to as connected vehicles (CVs) (V2X). The advancement of connected vehicle technologies makes widespread use of autonomous vehicles much more feasible. Connected and autonomous vehicles can not only provide real-time traffic data to aid traffic state estimation, but they can also act as traffic control executors, influencing traffic flow propagation directly, potentially improving traffic safety and mobility while also lowering energy consumption and emissions (Guo et al., 2019). potentially improving traffic safety (reduction/elimination of crashes) and mobility (i.e. travel time decrease) while also lowering energy consumption and emissions (Guo et al., 2019).

In the context of traffic management and urban traffic control, one of the main achievements that can be obtained with the incorporation of CAVs is the simultaneous optimization of vehicle operations and signal/timing phases to improve the performance of traffic flow at intersections (Guo et al., 2019). This problem is reffered to as Signal Vehicle Coupled Control. In this deliverable, we will focus on this optimization problem within the area of Adaptive traffic control and CAV. A more detailed definition of the problem as well as a description of their main components is provided in the following paragraph.

3.1.2 Signal vehicle coupled control (SVCC) for CAVs in urban environments

In metropolitan settings, signalized crossings are critical for improving traffic efficiency and vehicle fuel economy. Meanwhile, as CAVs advance, the mixed traffic environment, which consists of traffic participants with varying levels of intelligence, will become a critical stage of the intelligent transportation system. As said above, Signal vehicle couple control (SVCC) can become a critical approach for optimizing traffic signal timing and driving trajectories of CAVs at the same time, with the goals of improving traffic efficiency and saving energy, considering changes in the mixed traffic environment. Within SVCC we can differentiate three main components: traffic signal and phase optimization, CAVs trajectory optimization and CAVs route scheduling and planning. Below, we give more details about each of these components.

3.1.2.1 Traffic signal and phase optimization

One of the primary goals of signal timing settings is to convey vehicles through an intersection safely and efficiently. To achieve this purpose, different users must be accommodated through a right-of-way assignment plan. The plan should be flexible enough to adjust to demand fluctuations. The performance of the intersection is influenced by a number of signal timing characteristics. Cycle duration, green time, change interval, phase sequencing, and other factors are among them. One of the quickest and most cost-effective ways to reduce intersection congestion and enhance traffic flow in metropolitan areas is to regulate traffic signal timing. As a result, the timing of the Traffic Signal Control (TSC) system must be updated to cope with current urban traffic situations (M. K. Tan et al., 2016), (Sabar et al., 2017), (Akcelik, 1981)

The optimization of the signalized intersection has long been a topic of discussion. Given the changing traffic environment, the foregoing advantages of CAVs can be used to improve the traffic performance at signalized junctions. Traffic signal and vehicle trajectory optimization were previously thought to be two separate research challenges. Traffic signal optimization has been intensively explored in the transportation field, with rapid innovation to keep up with increasing traffic needs (Guo et al., 2019). Typically, researchers treat traffic signal management as an optimization issue based on certain traffic model assumptions (Z. Wang, Bian, et al., 2020), (Z. Li et al., 2014), such as the well-known adaptive traffic signal controllers, SCOOT or SCATS (Hunt et al., 1981, p.), (R, 1982).

As (L. Li et al., 2014) point out, a general arterial traffic control problem can be formulated as an optimization problem, with various state variables and environment inputs represented as set of variables. Over a finite time, horizon, the goal is to optimize a specific performance index. This performance index generally refers to mobility or sustainability goals, or a combination of the two. A sequence of control input is used as decision variables. Initial conditions, traffic flow dynamics, and vehicle dynamics are all constraints for the problem design.

3.1.2.2 Trajectory optimization

Due to their slow-responding, error-prone, uncooperative, and uncertain driving behaviors, human-driven vehicles in road traffic cannot be accurately managed or optimally coordinated. This has a number of negative consequences for road traffic performance and individual driving/riding experiences, including severe traffic congestion (Breton et al., 2002), high fuel consumption (Schrank et al., 2015) and heightened safety risks. Vehicle trajectory control systems have been proposed to address these concerns by establishing an appropriate speed profile for cars to follow. This improves traffic movement, fuel efficiency, and travel safety. The goal of CAV trajectory optimization problems is to improve specific objective functions (e.g. related to fuel consumption, emissions, safety, etc.) by keeping the vehicle trajectories within their feasible ranges. The trajectory optimization planning can be categorized into four main categories, basic car-following (Jiang et al., 2017), car following with bottlenecks (Zohdy & Rakha, 2016), car following with vertical control (Jin et al., 2016) and car following with lane changing (Bai et al., 2017). The decision variables, that refers to the vehicle movement, can include not only dynamic variables (such as position, speed, and acceleration), but also pedal and throttle adjustments, as well as steering wheel adjustments. Furthermore, the critical safety constraint connects the leading and trailing vehicles and ties many vehicles into interdependent traffic stream parts.

3.1.2.3 Route planning and scheduling

In addition to traffic signal control and CAV trajectory optimization, the CAV scheduling problem is frequently studied in research. (Hausknecht et al., 2011) expanded AIM from a single intersection to a network of intersections, where CAVs used several navigation algorithms to adjust their travel routes based on real-time traffic circumstances. Another multi-agent system proposed by (Jin et al., 2012) to schedule all CAV trips at intersections. CAV departure times and trajectories are tuned to reduce overall system travel time. According to real-time traffic circumstances, (Hassan & Rakha, 2014) devised a heuristic distributed coordination method that selected the head vehicles in approaching lanes to be the schedulers of CAV flows. Their goal was to reduce the average time spent waiting at intersections. To optimize overall network trip time, (Zhu & Ukkusuri, 2015) devised a lane-based linear formulation to enable autonomous intersection control, as well as dynamic departure time and route selections. They devised a set of constraints to eliminate flow propagation conflicts on lane connections, with flow propagation based on system-optimal network routing. To govern network-wide CAV flows, (Tettamanti et al., 2017) presented a two-level control technique. At the lowest level, a nonlinear model predictive control was used to optimize accident-free speed profiles for all CAVs near intersections. By managing link priorities, the upper-level challenge attempted to balance flow distributions across all links.

CAVs approach from opposite directions and have different destinations, therefore their trajectories will invariably cross in the intersection's centre. As a result, one of the most important functions of junction management is to stagger the arrival times of CAVs. The most straightforward option for scheduling CAVs approaching intersections is to use a first-in-first-out (FIFO) strategy, in which the CAVs that enter first are scheduled to exit first (Malikopoulos et al., 2018), (Dresner & Stone, 2008). Reservation-based (Dresner & Stone, 2004), batch-based (Tachet et al., 2016) and platoon-based approaches (Jin et al., 2013) all use similar concepts. These ad hoc scheduling strategies, while having a low computational overhead, are less likely to produce a high-efficiency scheduling plan. As a result, the literature indicates the need for optimization-based solutions for resolving the scheduling issue. The longitudinal and lateral control schedule for CAVs needs to be formulated as an optimization problem for reliable and optimal solutions.

3.2 Synchronization of on-demand with transit modes

3.2.1 Introduction

Due to the high use of motor vehicles, many cities and urban areas are facing important congestion problems. To address this issue, many authorities are promoting the use of public transport as it makes more efficient use of transportation infrastructure. However, due to the limited public transport coverage and infrequent service, especially with transit modes, many passengers, and particularly commuters, suffer what is called the first/last mile problems for transit. This problem is particularly acute in sparsely populated areas such as peri-urban or rural areas. Some proposed solutions to address this problem are park-and-ride facilities, taxi/carpooling, or the possibility of cycling to the transit station (Kumar & Khani, 2021). Shared and on-demand mobility have risen in recent years as a potential solution for the first/last mile transit problem.

Shared mobility systems for people transportation attempt to reduce the number of used automobiles, and hence traffic congestion and pollution, by minimizing the number of vacant seats in vehicles. Ridesharing, carpooling, vanpooling, car-sharing, dial-a-ride, and other concepts can be used to accomplish this. While shared mobility has several advantages, some studies show that the increasing use of some of these services may be shifted from the transit services (Masoud et al., 2017; X. Wang et al., 2018).

In this sense, shared and on-demand mobility and public transportation can, in fact, work together. On the one hand, shared and on-demand mobility can act as a feeder system for public transportation in less heavily populated areas. On the other hand, public transportation can broaden the scope of shared and on-demand mobility.

In line with this, this section, focuses on the synchronization of different shared- and on-demand mobility modes with public transport. Concretely, in the next subsections we will first review the main shared- and on-demand transport modes and business models that are used in combination with public transport, and the main optimization problems associated with them. Following, we will present a summary of the most relevant optimization problems we face when integrating and synchronizing these emerging mobility services with public transport to solve the first/last mile problem.

3.2.2 Main shared and on-demand mobility modes and related optimization problems

3.2.2.1 Rides-sharing

People without cars (or those merely wishing to save money on gas or share companionship on the journey) have long relied on sharing a ride with a friend or co-worker to get where they need to go. This mode of shared mobility is often tokened as ride-sharing. At its most basic level, ridesharing entails adding more passengers to an already-planned trip. Different forms of ride-sharing include (*Latest CIVITAS Policy Note*, s. f.):

- Carpooling, in which typically, travellers share a trip in a privately-owned. Carpools are frequently utilized for commuting.
- Vanpooling is a type of collective transportation that allows groups of commuters (often co-workers) to share a ride to and from work. Vanpooling is similar to carpooling, but it involves the use of larger vehicles, which are frequently provided by employers.
- Real-time or dynamic ridesharing: it is based on a mobile app or similar that links drivers and passengers according to their destination before the trip begins.

Ride-sharing has several advantages, including reduced travel costs and time, lower fuel and energy usage, reduced traffic congestion, and consequently lower air pollution. The ridesharing problem has several variations, the majority of which produce effective mobility solutions that allow travellers to share their journeys and thus improve their travel experience (Agatz et al., 2012). The two types of ridesharing planning are 'prearranged' or 'static' ridesharing and 'dynamic' ridesharing. Travellers' demand (drivers and riders) is known in advance (i.e., travellers' origins, destinations, and departure and arrival dates are given in advance) and can thus be utilized to plan their shared travels. Pre-arranged services are mostly utilized to plan regular commuter trips as well as shared long-distance journeys (e.g. inter-city trips). Long-distance journeys, on the other hand, tend to have more flexible time schedules than commuting trips. Drivers and riders are matched on-the-fly in dynamic ridesharing. In other words, new drivers can offer rides at any time, riders can request rides at any time, and the system will try to match their trips as soon as possible (or even en route). (Agatz et al., 2012) focused on the optimization problem of efficiently matching drivers and passengers in their evaluation of dynamic ridesharing systems. There are two steps to this ride-matching dilemma. The first step is to calculate effective vehicle routes. The second step, assigns passengers to those routes while balancing the competing goals of increasing the number of matched travellers while reducing operating costs and passenger annoyance.

3.2.2.2 Bike-sharing

Bike-sharing systems (BSSs) are becoming more popular as a means of achieving low-carbon and sustainable transportation since they can cut travel expenses, traffic congestion, and greenhouse gas emissions (Chen et al., 2018). Bike-sharing refers to the practice of community shared use of a bike in a time-sharing manner. The BSS ecosystem can be classified into four categories based on its operational model (*Latest CIVITAS Policy Note*, s. f.):

- Station-based, where users can take up and return bikes from IT-enabled docks or stations located across a service area with dock-based systems. This is the most common type of public bicycle sharing system.
- Dockless or GPS-based systems, in which bike locks are commonly included with bikes, allow riders to lock them to any public bike rack within a designated service area.
- Low-cost, tech-light systems, that do not have any technology in the bike or dock. Instead, users often sign up online and then receive a text or email with a code to unlock the bike's lock or gain access to a keyed lock box.
- Peer-to-peer bike sharing allows users to rent or borrow bikes from people or bike rental establishments on an hourly or daily basis.

Despite its effectiveness, the BSS is plagued by a supply-demand imbalance. This happens when a user arrives at a station and there are no bikes or parking spaces available. During morning rush hour, users pick up the bikes in residential neighbourhoods, ride them one way to work, and then return them. Because of the morning rush, there is high supply of bikes in working districts, however, not enough bikes are available in residential regions, and vice-versa in the afternoon peak time. Because the BSS has a limited probability of completing self-balancing in a short period, this mismatch results in poor service levels and low customer satisfaction. The bike-sharing rebalancing problem (BRP) (Fricker & Gast, 2016) requires the BSS operator to achieve a rebalance between bike supply and user demand by relocating bikes from excess stations to deficiency stations with the use of trucks to improve service level. This BRP problem is the most relevant problem in BSS. According to whether or not user interaction is minimal, BRPs can be classified as static or dynamic (Jia et al., 2020).

3.2.2.3 Demand-responsive transport

Demand responsive transportation (DRT) services are frequently viewed as a viable solution to the inadequate mobility of certain groups, such as the elderly and the disabled (Laws et al., 2009; Mageean & Nelson, 2003; Velaga et al., 2012). DRT is a sort of mobility service that "falls somewhere between the private vehicle and traditional public bus services" (Brake et al., 2007). DRT is also known as 'flexible transport service' and 'paratransit.' DRT is based on the concept of 'on-demand,' which means that travelers can request pick-up and drop-off based on their specific needs. Because of this broad definition, there are several variations and possible configurations of a DRT service in terms of scheduling, routing, vehicle type, and target group (Brake et al., 2007). DRT can be less expensive than taxis, especially if it is subsidized or allows for ride-sharing with other passengers (Ryley et al., 2014). Furthermore, DRT is viewed as a sort of service that supplements or replaces existing public transportation services and is connected with lower costs than traditional public (Enoch et al., 2004).

The optimization of demand-responsive transportation operations is usually addressed as a Dial-a-Ride Vehicle Routing Problem in which the goal is to construct a set of routes that will meet passenger demands at the lowest possible cost (Masson et al., 2014; Ritzinger et al., 2016). Each request entails transporting a passenger from his or her origin to his or her destination, with passengers with the similar route and time choices using the same vehicle as long as space is available. As a result, limiting overall travel distance and hence travel time while satisfying rider-specified time limits and any vehicle restriction constraints is key to solving the DARP. The shared-taxi problem, presented by (Hosni et al., 2014) as a multi-vehicle dynamic DARP, is another form of the ridesharing problem. Passengers in the shared-taxi problem choose their preferred pickup and drop-off locations, as well as the earliest/latest permissible pickup/drop-off time and a maximum journey time.

3.2.3 Integration of shared and on-demand mobility with public transit modes

The major optimization problems concerning the integration of shared and on-demand mobility are related to timetable synchronization, fleet sizing and rebalancing. Synchronization of timetables is an effective method for reducing transfer waiting times and improving service connectivity. Consideration of user demand and vehicle schedules along with public transit timetable synchronization archives better practical solutions. For ridesharing, the main challenge for synchronization lies in the manageability of individual riders in the shared vehicle but for DRT, the main challenge is to match the schedules of the riders along with that of the public transit systems like train, metro etc. This scheduling problem can further be extended to different classes of problems like:

- Driver-rider scheduling (Kumar & Khani, 2021; Stiglic et al., 2018), where the aim is to find the appropriate driver to match the rider demand and it is a very common problem in carpooling as well as ride-hailing scenarios.
- DRT to transit scheduling (Auad-Perez & Van Hentenryck, 2022; Y. Liu & Ouyang, 2021; Luo et al., 2021), where the aim is to find an appropriate instance solution which matches DRT time schedule with public transit etc.

Apart from this, another kind of problem can be found in the literature that deals with the integration of shared/on-demand mobility with transit modes, it is the fleet size optimization, and it is associated with calculating the number of shuttles required to fulfil the appropriate performance metrics like the minimum operational cost or the maximum network utilization. Fleet size optimization is heavily influenced by the factors like historical demand, weather conditions, planned events and unplanned events. Authors in (Wallar et al., 2019) considered historical demand data to determine how many vehicles are needed and the optimal trip initialization location along with the feasible route to maximally satisfy the trip demand of any given time. Rebalancing problems are common among micro-mobility platforms such as bike-sharing (Jia et al., 2020) and aim to find an optimum balance between different bike station restocking as per user demand.

3.3 Dynamic congestion pricing

3.3.1 Introduction

Following the definition given in (Saharan et al., 2020), congestion pricing is a transportation policy in which prices of goods, infrastructure or services change using some method or algorithm that considers the demand and supply, competitor pricing and other historical or current external factors of the market (Saharan et al. 2020). When static pricing is applied in an environment which does not change with respect to any involved parameter, then it returns a fixed profit. However, when static pricing is applied to the dynamic environment which changes with respect to involved parameters, it may lead to a loss if the profit margin is not big enough. Dynamic pricing addresses such situations very well and takes care of everybody's interest.

In the context of Intelligent Transportation Systems (ITS), Dynamic congestion pricing – DCP (Lombardi et al., 2021) is a variant of congestion pricing where prices vary dynamically in real-time as a function of current traffic conditions. This approach is opposed to flat pricing, which stays constant over time, and scheduled pricing, where tolls vary by time of day, day of the week or season following a predetermined schedule. Among the benefits of dynamic congestion pricing are the reduction of traffic on specific roads, the maintenance of average speed, the promotion of carpooling and public transportation, the restriction of a particular type of vehicle, the restriction of traffic at specific times and on specific occasions, the generation of revenue, and the balance of cost between payer and payee.

According to (Saharan et al., 2020), the main elements of dynamic congestion pricing are current parameters, history of parameters and prices, dynamic pricing strategy, and prices. Within the parameters, different components can be considered: transportation demand and supply, time of the day, weather conditions, and culture, among others. These factors may change over time together with the prices associated with the dynamic pricing policy. Such change represents the history of parameters and prices. In the following subsections, we review the main dynamic congestion pricing optimization models (Within-day and Day-to-day) and the main dynamic pricing schemes (Zonal-based, Cordon-based and Distance-based).

3.3.2 Dynamic congestion pricing optimization models

3.3.2.1 Within day Dynamic Congestion Pricing optimization

Within-day DCP models aim to determine time-varying tolls on the within-day timescale to ease traffic congestion and enhance social welfare. The latter assumes that travellers decide their route choices and departure times in a selfish manner (Chung et al., 2012). The majority of DCP models are written in the form of bi-level programming models or mathematical programming models with equilibrium restrictions. The objective function in these models can be established by reducing overall system travel times, maximizing total system benefits, or optimizing the limitations of each individual's dynamic route choice and departure time decisions. As a result, the DCP optimization can be thought of as a dynamic user equilibrium (DUE) problem.

3.3.2.2 Day-to-day Dynamic Congestion Pricing optimization

According to (Z. Tan et al., 2015), the general aim of day-to-day DCP is to achieve system optimality by considering travellers' day-to-day route choice behaviour in avoiding costly routes. However, DCP with day-to-day route flow evolution has received only limited attention in the literature. The contributions reported in the state-of-the-art are directed towards a continuous DCP with travellers' reasonable day-to-day route choice adjustment behaviour (Sandholm, 2002). For example, (Friesz et al., 2004) proposed a DCP scheme considering the day-to-day route flow adjustment process over a planning period. This scheme requires a reliable forecast of the traffic flow and the link cost function as well as the OD demand function. In (F. Yang et al., 2007), the authors considered the convergence speed of the DCP and proposed a day-to-day DCP scheme which could strongly expedite the system to optimal in terms of maximizing the reduction of total system travel cost on each day.

3.3.3 Dynamic congestion pricing schemes

3.3.3.1 Zonal-based Dynamic Congestion Pricing

This dynamic congestion pricing scheme is defined by a bounded area where vehicles should pay a congestion toll to enter or exit this area, or to travel within it without crossing its boundary (de Palma & Lindsey, 2011). The boundary of the charging area can be defined according to natural features such as lakes, mountains, as well as the specific urban delimiters such as tunnels, roads, and bridges.

The world's first congestion toll scheme, which is known as Area Licensing Scheme, was implemented in Singapore in 1975: it is a typical zonal-based pricing scheme (Seik, 1997). The congestion pricing policy achieved a huge success in easing traffic congestion, and the total traffic volume in the toll area was reduced by 45% after the implementation of this zonal-based congestion pricing policy. Other implemented zonal- based congestion pricing scheme to be highlighted is the London Congestion Charge, established in 2003 (de Palma & Lindsey, 2011).

According to the state-of-the-art, the priority for zonal-based pricing is to find the optimal toll charging rate under day-to-day or daily DCP schemes. Thus, from an optimization perspective, this congestion charge rate is the main decision variable to model this type of DCP problem. In addition, in these studies, the optimization is oriented to increase the revenue coming from the pricing scheme, while reducing the operational costs of this DCP policy.

3.3.3.2 Cordon-based Dynamic Congestion Pricing

Cordon-based pricing scheme is a specific zonal-based pricing scheme, while the toll area is a single bounded cordon or multiple cordons. In its strictest sense, Singapore's ERP, which was introduced to replace the Area Licensing Scheme in 1998, is a hybrid of facility-based pricing and cordon-based pricing scheme (de Palma & Lindsey, 2011). Toll rates are generally varied by vehicle types, time of day, and location of the gantry, making it a DCP scheme (Z. Liu et al., 2013).

Another relevant cordon-based DCP system is the one test in Stockholm from January 2006 to July 2006. After this trial, public support increased from about 20-25% to 53%, which resulted in a reimplementation of congestion pricing in 2007 but only after a referendum (Eliasson, 2008; Eliasson et al., 2009). The traffic reduction, compared with levels measured 12 months earlier, stabilized after one month into its implementation at around 22% (Eliasson et al., 2009) Norwegian cities and Milan (Italy) have also cordon-based schemes; however, they are proposed either for revenue generation or emissions reduction, not congestion alleviation.

Apart from the cordon-based schemes reported in transportation literature, this type of DCP policy is quite similar to the case of zonal-based pricing. Therefore, the optimization of this kind of problem shares similar decision variables and constraints concerning the zonal-based case.

3.3.3.3 Distance-based Dynamic Congestion Pricing

With distance-based schemes, charges vary with distance travelled, either linearly or nonlinearly. As noted before, some facilities charge based on distance. Networks of truck-only toll lanes and networks of High Occupancy Toll (HOT) lanes are under consideration, and tolls on these networks are likely to be distance-based as well. For schemes that encompass multiple roads or regions, the charge rate can depend on the type of road. According to the existing literature, all implemented distance-based schemes are adopted for heavy goods vehicle lanes (e.g. in four states in the USA and some European countries such as Switzerland, Germany, Austria, Slovakia, and the Czech Republic) and truck-only toll lanes (Conway & Walton, 2009; de Palma & Lindsey, 2011) Recently, some researchers have shown how distance-based congestion pricing schemes can alleviating traffic congestion in urban areas due to their greater fairness and effectiveness (Daganzo & Lehe, 2015; Z. Liu et al., 2014; Meng et al., 2012).

Having said that, in distance-based dynamic congestion pricing the optimization is usually focused on finding the distance-toll function or the congestion charging rates that maximize the system performance or minimize the system costs or system externalities (e.g. emissions).

4 Optimization models and techniques for Transport Network Management

The objective of this section is to describe the literature reviewed regarding the three problems mentioned in Section 3, that is, Signal Vehicle Coupled Control with CAVs, Synchronization of shared and on-demand mobility with transit modes, and Dynamic Congestion Pricing. At the beginning of this section, we overview the background concepts like, optimization modelling approaches and methods is presented. Following that, we describe the criteria used for literature classification. And final, the main part of this section is devoted to describing the literature reviewed for the three problems according to the mentioned criteria and listing the main gaps that we identified in each of the problems.

4.1 Background

The objective of this section is to provide background information to facilitate the understanding of the following subsections. To this end, we briefly define the main components of an optimization model, some of the most known optimization modelling approaches, metaheuristics and statistical learning.

4.1.1 Optimization models

The first step in performing an optimization is to formulate the problem appropriately. An optimization problem is defined by four parts:

- **Decision variables:** The decision variables of an optimization problem refer to a set of variables whose domain of values changes to find an optimal solution to the given optimization problem. Therefore, a solution for an optimization problem is a set of values assigned to the decision variables.
- **Constraints:** In the context of optimization, the constraints are the bounds on functions of the decision variables. The latter means that the constraints specify which solutions are feasible within the definition of the optimization problem under consideration.
- **Objective function:** The Objective is a function of the decision variables previously defined. It gives a single number evaluating a possible solution, which an optimizer tries to minimize or maximize depending on how the user has defined the optimization model. For instance, in a linear program, the objective is defined by a set of coefficients or weights that apply to the decision variables; meanwhile, for a nonlinear program, the objective function can be any expression or variable that depends on the decision variables.
- **Bounds on the decision variables:** These bounds define the set of possible solutions, called the search space. Each decision variable can have a lower bound and/or an upper bound.

4.1.2 Optimization modelling approaches

Some of the most used and known optimization modelling approaches are the following:

- **Linear programming (LP)**, where the objective function must be a linear function of the decision variables.
- **Quadratic programming (QP)**, where the objective is a quadratic function and the constraints must be linear functions of the decision variables.
- **Quadratically-constrained program (QCP)**, where the objective function and constraints must all be linear or quadratic functions of decision variables.
- **Nonlinear programming (NLP),** where the objective function or any of the constraints are non-quadratic in any of the decision variables.

- **Bi-level programming:** Bilevel programs are mathematical programs with optimization problems in their constraints. The main problem is called the upper-level problem or the leader and the nested problem is called the lower-level problem or the follower. A simple example is the bilevel programming problem that optimizes an upper-level objective over constraints that include a lower-level optimization problem(Sinha et al., 2018).

4.1.3 Metaheuristics

The growing computational capabilities and the fact that some problems of great practical value (e.g., scheduling, routing, facility location) cannot be solved optimally (because they are NP-Hard problems) have led to increased use of approximating algorithms. Meta-heuristics are a suitable approach in situations where exact algorithms cannot give an answer using a reasonable amount of time or memory (Bianchi et al., 2009). These methods arose with the idea of extracting the best parts of different successful heuristics to create generic methods that could be applied to a more significant number of problems and contexts. Due to the wide variety of meta-heuristics, different classification categories have been proposed (Blum & Roli, 2003). A usual classification is the one that groups meta-heuristics in Evolutionary Computation (EC) (Foster, 2001), Swarm Intelligence (SI) (Chakraborty & Kar, 2017), and other meta-heuristics (e.g., local search-based meta-heuristics) (Martello et al., 1999). These groups are presented in more detail as follows.

EC is a group of meta-heuristic optimization algorithms inspired by biological evolution (e.g., Genetic algorithms, Differential evolution). Within this family of methods, they operate from an initial set of candidate solutions (initial generation), which are updated in an iterative way. Then, each new generation is generated by randomly removing candidate solutions according to predefined criteria and by inserting random changes. After a set of iterations, the population of solutions will gradually evolve to increase its competitiveness, framed by a fitness function that is determined by each algorithm. Following the described procedure, EC algorithms can produce highly optimized solutions for complex real-world optimization problems like the travelling salesman problem (Bektas, 2006).

The second biggest category of meta-heuristics is the category of SI (e.g., Ant Colony, Particle Swarm). This approach consists of a population of agents interacting with each other and their environment. The agents follow a set of basic rules, and although there is no centralized control structure guiding the agents on how they should behave, the interaction between them leads to the emergence of intelligent global behaviour. SI is inspired by biological systems such as ant and bee colonies and is commonly used to solve combinatorial and continuous optimization problems. Lastly, the third category groups together the rest of the meta-heuristics, which are outside of the domains of EC and SI but are still relevant for solving optimization problems. For example, this is the case for local search-based meta-heuristics that are focused on finding a solution that maximizes a criterion among a set of candidate solutions. These meta-heuristics move from one solution to another in the search space of candidate solutions by applying local changes until an optimal solution is found or a time budget is reached.

4.1.4 Machine Learning

Machine Learning (ML) methods are algorithms that are able to learn a specific task without being explicitly programmed. More formally, according to Mitchell (Jordan & Mitchell, 2015), these types of methods learn from experiences *E*, related to a task *T*, and their performance is evaluated by a metric *P*. The performance in *T* improves according to *P*, with experience *E*. Classically, these methods can be classified according to the three basic learning approaches reported in the literature: unsupervised learning, supervised learning, and reinforcement learning. Within the TANGENT project, we will be focused only on supervised learning approaches.

Supervised learning is the other fundamental area of Statistical Learning methods (Marsland, 2014). It consists of algorithms that learn a function $f: X \rightarrow Y$ by training with a finite number of input-output pairs, *X* being the input domain and *Y* the output co-domain. This learning stage can be seen as *E* in Mitchell's definition (Jordan & Mitchell, 2015), and the specific task *T* usually involves predicting an output given a new and unseen input (Charte et al., 2019). Common families of methods that stand out in supervised learning are decision tree-based (e.g., Decision Tree, Extra Trees), instance-based (e.g., K-Nearest Neighbors), kernel-based (e.g., Support Vector Machine), or ensemble-based methods (Random Forest, AdaBoost). Supervised learning problems can usually be divided into classification and regression (Jain et al., 2000). In both cases, the basis is an input data-set, *X*, and their difference is the type of target variable, *Y*, to be predicted. In the classification case, *Y* is divided into discrete categories, while in regression, the aim is to predict continuous values. Standard classification problems can be either binary or multi-class problems (Duda et al., 2001). In the former case, an instance can only be associated with one of two values: the positive or negative equivalent to 0 or 1; whereas, in multi-class problems, there are more than two classes under consideration. A multi-class problem means that a given instance belongs to one of the multiple possible categories. Diversely, a supervised regression problem (Smola & Schölkopf, 1998) consists of finding a function that can predict, for a given example, a real value in R.

4.2 Description of the criteria to classify literature

This section aims to describe the criteria we have used to classify the literature reviewed around the three areas of optimisation that are the focus of this deliverable: Signal Vehicle Coupled Control, Integration of shared and on-demand mobility and public transit modes, and Dynamic congestion pricing. We have defined a set of criteria to extract relevant information from every study area from an optimization perspective. These criteria are exposed in the figure presented below. Besides, within each study area, there are specific criteria that only apply to describe a single problem domain; these other criteria are introduced in the text below.

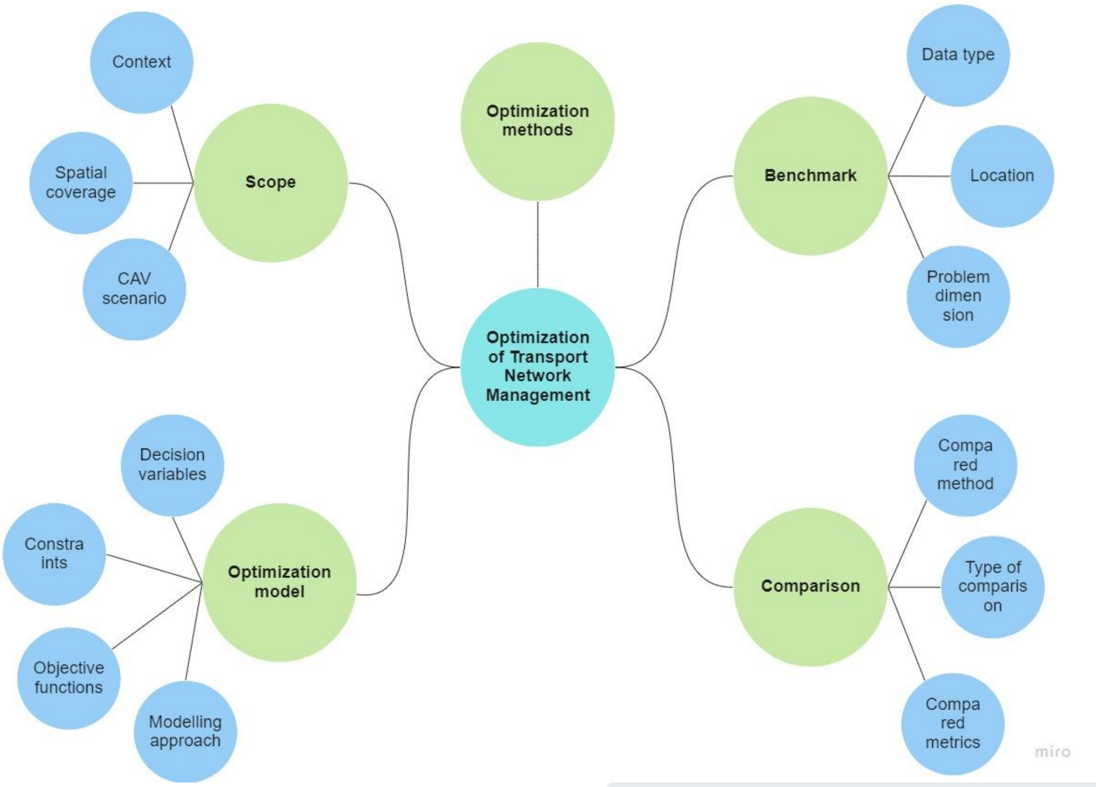

Figure 1: Criteria to classify literature regarding Signal Vehicle Coupled Control, Integration of shared and on-demand mobility and public transit modes, and Dynamic congestion pricing

- **Scope:** This attribute consists of the context of the optimization network, the transportation modes and the CAV scenario considered. Below we describe each of these sub-attributes:
    - **Context:** This sub-attribute refers to the context of the transportation network in which the optimization problem takes place: Urban, Metropolitan area, Inter-urban.
    - **Transportation modes:** This sub-attribute represents the transportation modes considered in the optimization problem: Private vehicles, Public transport, Cycling, Pedestrian, etc.
    - **CAV Scenario**: This scenario refers to the CAV scenario considered in the Network Optimization Problem: Only conventional vehicles, Mixed traffic, High penetration of CAVs
- **Optimization model:** This attribute defines the different elements of the modelling of the optimization problem, as the decision variables, constraints, objective function and mathematical modelling approach:
    - **Decision variables:** Definition of the decision variables considered in the problem
    - **Variables domain:** Domain of the variables (i.e. continuous, integer, binary, combinatorial)
    - **Constraints:** Main constraints considered in the optimization problem.
    - **Architecture (Only applicable for SVCC problem category):** Centralised or Decentralised
    - **Control Level (Only applicable for SVCC problem category):** Multiple vehicle or individual vehicle.
    - **Objective function/performance measures:** Objective function or performance measures to be optimized
    - **Modelling approach:** Modelling approach used for the formulation of the optimization problem (ex. Mathematical programming, simulation, etc).
- **Optimization method:** This attribute refers to the optimization method used to find the optimal or near-optimal solutions for the problem (e.g. Mathematical programming solver, meta-heuristics, heuristics, etc.)
- **Benchmark:** This attribute aims to describe the specific benchmark or optimization problem instances used to validate the optimization models and methods proposed. We consider the next three sub-attributes:
    - **Type of data:** It refers to the nature of the data used. The possible categories are: Synthetic data, Real data, Mixed.
    - **Location:** it indicates whether the location from which the data originates is real or virtual.
    - **Dimension of the problem:** Dimensionality or size of the optimization problem is measured by the number of decision variables.
- **Comparison:** This attribute indicates the existence of a comparative study in the paper.
    - **Type of Comparison:** Scheme of comparison used in the paper: no comparison study, self-comparison with different parameter settings or comparison with another baseline algorithm/s.

- **Compared methods:** Names of the methods that are considered in the comparative study.
- **Metric for comparison:** Metric used for comparison.

4.3 Optimization models and techniques for Signal-vehicle Coupled Control (SVCC)

The main objective of this section is to discuss and categorize the literature reviewed around optimization models and techniques proposed to deal with the optimization of Signal-vehicle Couple Control.

Following that, Section 4.3.1 reviews the application scope of the reviewed papers. Section 4.3.2 introduces the optimization models that are often reported in the literature. These models incorporate decision variables, restrictions, cost functions, and modelling approaches. Section 4.3.2 summarizes the most typical optimization procedures for dealing with the previously specified optimization models. The important aspects of the experimental benchmarks (e.g., data type, location, problem dimension, and so on) that are typically used to evaluate optimization approaches for addressing challenges are then discussed in sections 4.3.3 and 4.3.4. Finally, section 4.3.5 highlights several literature gaps linked to the modelling approach.

4.3.1 Application scope

Context: most of the papers focused on an urban scenario (Du et al., 2021; Z. Li et al., 2014; Niroumand et al., 2020; Qian et al., 2021; C. Sun et al., 2020; Tajalli et al., 2021; Y. Wang et al., 2019; Yu et al., 2018, 2019), and only few of them, considered peri-urban areas (X. Li et al., 2018; Ma et al., 2017; Zhou et al., 2017).

Spatial coverage: we observed that the majority of the papers reviewed (Du et al., 2021; X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Niroumand et al., 2020; C. Sun et al., 2020; Yu et al., 2018; Zhou et al., 2017) focus on intersections, with few papers considering corridors (Z. Wu et al., 2021) or the complete transport network (Qian et al., 2021; Tajalli et al., 2021).

CAV scenarios: most of the papers focus on scenarios with a high penetration of CAVs (X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Qian et al., 2021; C. Sun et al., 2020; Tajalli et al., 2021; Y. Wang et al., 2019; Yu et al., 2018, 2019; Zhou et al., 2017). Only (Du et al., 2021) and (Niroumand et al., 2020) discuss the application of the SVCC problem to mixed traffic.

4.3.2 Optimization models

Architecture: Architecture describes the system design for the considered optimization problem. The majority of the articles that we reviewed (X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Niroumand et al., 2020; Qian et al., 2021; Tajalli et al., 2021; Yu et al., 2019; Zhou et al., 2017) considered centralized architecture for the SVCC optimization problem. Only three articles (Du et al., 2021; C. Sun et al., 2020; Yu et al., 2018) considered a decentralized optimization approach.

Control Level: According to state-of-art literature, most of the articles (X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Niroumand et al., 2020; Qian et al., 2021; Tajalli et al., 2021; Y. Wang et al., 2019; Yu et al., 2018, 2019; Zhou et al., 2017) consider multiple vehicle control as the control level of the problem. We found only two articles (Du et al., 2021; C. Sun et al., 2020) that considered individual vehicle-based control strategies.

Decision Variables: Amongst several reported decision variables in the literature, vehicle dynamics and signal timings are majorly used decision variables. Vehicle dynamics couples multiple vehicular parameters like acceleration and de-acceleration rate, drive-train ratio, etc. (Du et al., 2021; X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Niroumand et al., 2020; Salazar et al., 2018; C. Sun et al., 2020; Tajalli et al., 2021; Zhou et al., 2017). Signal timing deals with the different time phases for the traffic signals (Du et al., 2021; Qian et al., 2021; C. Sun et al., 2020; Yu et al., 2018).

Apart from the above described two variables, there are three more of them which are being used, but to a lower extent, as building blocks for the SVCC optimization problem in the literature. Vehicle trajectory which controls the path a vehicle follows at any time point, (Qian et al., 2021; Yu et al., 2018, 2019), travel route (Qian et al., 2021) and departure time (Qian et al., 2021).

Constraints: According to the literature reviewed, it can be observed that there are some common limiting factors like fuel consumption and route feasibility which act as constraints in several SVCC models (Du et al., 2021; Z. Li et al., 2014; Qian et al., 2021; C. Sun et al., 2020; X. T. Yang et al., 2021; Yu et al., 2018). Signal timing synchronization which deals with the overhead related to matching different signal phase timings is another factor prevalently being used in the literature (Du et al., 2021; Qian et al., 2021; Yu et al., 2018) as a design constraint during the optimization problem formulation.
Another common constraint that can be found in literature is related vehicle communications (e.g. V2V or I2V). Concretely, communication overhead is another factor that has been used as a constraint in literature (Du et al., 2021).

Objective Functions: We can group the potential objective functions into three broad categories. The first category is concerned with traffic flow efficiency, and under its aegis we found various metrics like vehicle delay (Yu et al., 2019), average waiting time (Du et al., 2021; Yu et al., 2018), vehicle throughput (Z. Li et al., 2014; Tajalli et al., 2021; Yu et al., 2019) etc. being used as the objective function for the optimization model. The second category of objective functions is related to safety. For example, we found trip safety to be addressed as an objective function in (Ma et al., 2017; C. Sun et al., 2020). The final class is concerned with the economic and environmental impact of the travel and under this category different metrics like total CO_2 emission (Du et al., 2021; Yu et al., 2018) or fuel-efficiency (Du et al., 2021; Ma et al., 2017; C. Sun et al., 2020).

Modelling Approach: Based on the modelling approach the literature can be classified into two main categories. The first one is mathematical programming, where we can find papers such as (X. Li et al., 2018; Niroumand et al., 2020; Qian et al., 2021; Tajalli et al., 2021; Yu et al., 2018, 2019) using, for example, mixed-integer programming. And the second one is simulation-based, which has been the approach used in (Du et al., 2021; Z. Li et al., 2014; C. Sun et al., 2020).

4.3.3 Optimization methods

The type of optimization methods can be broadly grouped into three groups, namely mathematical programming solvers, heuristic-based solvers, and experimental-based optimization. In the mathematical programming solvers category, (Qian et al., 2021) proposed a method using CPLEX to optimize the departure times, travel routes and longitudinal trajectories of CAVs, and authors in (Yu et al., 2019) and (Yu et al., 2018) proposed another mathematical optimization based an approach using Gurobi to optimize CAVs trajectory and signal timings. To optimize the driving control of CAVs in signalized intersections authors in (C. Sun et al., 2020) used dynamic programming as an optimization tool. Authors in (X. Li et al., 2018) used a bisecting search-based algorithm to optimize the trajectories of CAVs.

Apart from these methods, during the literature review, we found that heuristic-based optimizers were also used for trajectory control for CAVs, like in (Ma et al., 2017; Zhou et al., 2017) authors proposed parsimonious shooting heuristics for optimal trajectory control of CAVs. Lastly, Experimental-based optimization has also been applied by other authors to solve SVCC optimization problems. It can also be seen that various traffic simulation tools like SUMO are being used as experimental optimization tools for the problem at hand (Du et al., 2021). Researchers in (X. Li et al., 2018) used a rolling horizon-based simulation using MATLAB. A mixture of mathematical programming with simulation platforms like VISSIM can be found in (Tajalli et al., 2021).

4.3.4 Experimentation/test Benchmark

Type of data used: as we can expect for this type of problem, given that we are dealing with futuristic scenarios, most of the works based their experimentation on synthetic data (Du et al., 2021; X. Li et al., 2018; Z. Li et al., 2014; Ma et al., 2017; Niroumand et al., 2020; Qian et al., 2021; C. Sun et al., 2020; Tajalli et al., 2021; Y. Wang et al., 2019; Yu et al., 2018, 2019; Zhou et al., 2017).

Location: In line with the issue mentioned above, most of the papers do not base their experimentation on a specific location, but on synthetically generated intersections, corridors or networks. Only two publications specify a real location, the city of Hangzhou in China (Qian et al., 2021) and Illionis (USA) (Tajalli et al., 2021).

Problem dimension (network size): Authors of (Qian et al., 2021) considered 46 nodes and 122 link-based networks for the simulation purpose. Single corridor with four intersections was considered in (Yu et al., 2019). Authors of (Yu et al., 2018) considered a four-arm intersection for simulation purposes whereas, authors of (C. Sun et al., 2020) considered two different simulation cases one with 3 and another with 7 signalized intersections. Works presented in (Ma et al., 2017) and (Zhou et al., 2017) targeted a highway segment as their simulation test ground. (Tajalli et al., 2021) considered a network consisting of twenty intersections. Apart from these works several others (X. Li et al., 2018; Z. Li et al., 2014; Niroumand et al., 2020) have just mentioned that they considered intersection but did not specify any details about it.

4.3.5 Comparison studies

Compared methods: Based on the literature reviewed, we observe that most of the studies include comparisons versus other optimization algorithms or models. For example, the authors of (Yu et al., 2019) compared their proposal versus coordinated fixed time control. In (Du et al., 2021), the authors have chosen two baselines namely CACC and GlidePath for comparison purposes. Apart from these, IDM and modified IDM have been used as baseline for comparison in literature (Ma et al., 2017; C. Sun et al., 2020). Newell’s solution with specific IVP settings is another common baseline (Zhou et al., 2017) for CAV trajectory optimization in the SVCC problem category. Authors in (Z. Li et al., 2014; Niroumand et al., 2020; Tajalli et al., 2021) used traditional actuated signal control as a baseline algorithm for their comparison. There are other works like (Yu et al., 2018) which use different parameter settings for baseline comparison without considering any external algorithm or benchmark. Authors in (X. Li et al., 2018) considered a parsimonious shooting heuristic algorithm (Ma et al., 2017) as their comparison baseline.

Comparison metrics: the most widely used metric for performance comparison in the literature reviewed was fuel consumption. Various studies like (Du et al., 2021; X. Li et al., 2018; Ma et al., 2017; C. Sun et al., 2020; Yao et al., 2020) have used this metric for comparison purposes. Other than that, total CO2 emission is another very metric used in the literature (Du et al., 2021; X. Li et al., 2018; Yu et al., 2018). Apart from these two, there are a few metrics namely average delay (Du et al., 2021; Niroumand et al., 2020; Yu et al., 2018, 2019), total throughput (Z. Li et al., 2014; Yu et al., 2019), average speed (Du et al., 2021), speed variation (Tajalli et al., 2021) and travel safety (Ma et al., 2017) etc. that can be found in the literature.

4.3.6 Research gaps and assessment of optimization models and techniques

This section aims to discuss the main research gaps we have identified in the reviewed literature. To do so, we will structure our discussion in terms of models, optimization methods, experimental framework and comparative studies.

Regarding optimisation models, the majority of the SVCC approaches examined in this deliverable were created to optimize traffic efficiency and/or environmental impact (e.g. reducing overall system travel time or fuel consumption, respectively). However, there are only a few studies that consider safety as one of the objective functions. Furthermore, many previous studies focused on just one goal, that is, on single objective optimization. However addressing numerous goals at the same time can increase overall control performance (Xu et al., 2017; Zhao et al., 2018). The main issues are: (1) how to choose specific and quantitative measures for various objectives; (2) how to integrate and balance several objectives with different units into one function; and (3) how to establish limitations for various objectives. In this sense, we expect future research to develop multi-objective SVCC models that consider the optimization of safety, system performance, and environmental impact, simultaneously.

Another important aspect of the modelling is the type of CAV scenario considered. Although CAV penetration is likely to rise substantially in the future, there is still a long way to go until completely automated cars or high CAV penetration are achieved. However, as mentioned above, only a few papers focused on scenarios that combine CAV with conventional vehicles in mixed traffic scenarios. This can be an important issue because some recent study results suggested that when the penetration rate exceeds 25–30%, the performance changes significantly (Hao et al., 2014; (Jeff) Ban et al., 2011).

In terms of the experimental framework, it should be noted that only a few articles examine corridor-level or network-level signal optimization and coordination, with the majority focusing on single crossings. Furthermore, the reviewed studies tend to focus on synthetically generated simplified road networks that do not take into account the complexity of real-world road networks, which might heavily skew the results of those research.

4.4 Optimization models and techniques for integration of shared- and on-demand mobility services with transit modes

Analogously to the previous section, the main objective of this section is to discuss and categorize the literature related to the integration of shared- and on-demand mobility services with transit modes.

Following that, Section 4.4.1 reviews the application scope of the reviewed papers. After that, this part introduces and reviews the essential components that are normally considered when creating an optimization technique for the synchronization of on-demand and transit traffic schemes. The optimization models that are commonly described in the literature are first presented in section 4.4.2. The decision variables, constraints, cost function, and modelling methodologies are all included in these models. The optimization strategies commonly explored for addressing the optimization models previously defined are summarized in section 4.4.3. Following that, sections 4.4.4 and 4.4.5 go over the key properties of the experimental benchmarks (e.g., data type, location, problem dimension, and so on) that are commonly used to evaluate optimization approaches for addressing issues. Finally, section 4.4.6 discusses a few gaps in the literature related to the modelling process and optimization.

4.4.1 Application scope

Context: the majority of the publications reviewed (Auad-Perez & Van Hentenryck, 2022; Costa et al., 2021; Gkiotsalitis et al., 2022; Jia et al., 2020; Kumar & Khani, 2021; Lau & Susilawati, 2021; Levin et al., 2019; T. Liu & Ceder, 2018; Y. Liu & Ouyang, 2021; Lu et al., 2020; Luo et al., 2021; Stiglic et al., 2018; B. Sun et al., 2019; L. Wu et al., 2020) considered <u>urban mobility context</u> in their problem formulation. We did not find any literature that considered rural or inter-urban scenarios as testing context.

CAV scenario: most of the studies review focus on the scenario with only conventional vehicles (Auad-Perez & Van Hentenryck, 2022; Costa et al., 2021; Gkiotsalitis et al., 2022; Kumar & Khani, 2021; T. Liu & Ceder, 2018; Y. Liu & Ouyang, 2021; Lu et al., 2020; Luo et al., 2021; Stiglic et al., 2018; B. Sun et al., 2019; L. Wu et al., 2020). Only two papers consider the synchronization of shared- and on-demand with public transit in the presence of CAVs (Levin et al., 2019), (Lau & Susilawati, 2021).

4.4.2 Optimization models

Decision variables: Related literature presents multiple decision variables amongst which, vehicle departure schedule is one of the most utilized decision variables. This variable deals with the detailed time schedule for any particular vehicle in a particular route. Some examples can be found in (Auad-Perez & Van Hentenryck, 2022; Gkiotsalitis et al., 2022; T. Liu & Ceder, 2018).
Apart from the vehicle departure schedule, drive-rider matching, which tries to match an available driver to the current needful traveller based upon vehicle availability and route feasibility, can be also considered as a decision variable in (Kumar & Khani, 2021; Stiglic et al., 2018).
Shared vehicle capacity consolidated the number of passengers that can be transported in one single trip abiding by all traffic rules. It has been used in (Jia et al., 2020; Levin et al., 2019; B. Sun et al., 2019; L. Wu et al., 2020) as a decision variable.

Constraints: Based on the literature review, it can be seen that there are some common constraints like the passenger's waiting time and total travel time limit which try to put boundaries over the time expenditure on a trip. It can be seen that these are being implemented as a limiting factor in works like (Costa et al., 2021; Jia et al., 2020; Lau & Susilawati, 2021; Levin et al., 2019).
Trip demand coverage, which consolidates the necessity of vehicles in a particular route to satisfy a predefined percentage of the demand, is presented in the literature (Auad-Perez & Van Hentenryck, 2022; Costa et al., 2021; Luo et al., 2021) as another design constraint in the formulation of these optimization problems.

Vehicle load (number of passengers per vehicle) and vehicle capacity (maximum number of passengers per vehicle) are also two commonly used constraints (Auad-Perez & Van Hentenryck, 2022, 2022; Jia et al., 2020; Lau & Susilawati, 2021; Levin et al., 2019; T. Liu & Ceder, 2018; Lu et al., 2020; Luo et al., 2021). Other less frequently used constraints are driver-rider matching (Kumar & Khani, 2021; Stiglic et al., 2018), passenger travel behaviour (T. Liu & Ceder, 2018) and location connectivity (Auad-Perez & Van Hentenryck, 2022; Luo et al., 2021).

Objective Functions: According to the literature review, there are three types of objective functions that are being used in state-of-art literature. The first of them is related to the system-wide costs, which deals with revenue generation and tries to maximize operator profit by minimizing operational cost and has been used in (Auad-Perez & Van Hentenryck, 2022; Gkiotsalitis et al., 2022; T. Liu & Ceder, 2018; Y. Liu & Ouyang, 2021; Lu et al., 2020; Luo et al., 2021). The second type of objective function are related to passenger travel time, as it aims to minimize the total travel time for a passenger. It has been used as an objective function in works like (Costa et al., 2021; Gkiotsalitis et al., 2022; Jia et al., 2020; Lau & Susilawati, 2021; Levin et al., 2019; B. Sun et al., 2019). The third category of objective functions that are prevalent in the literature is related to optimal driver-passenger matching, where the goal is to find best possible (in terms of feasible route, timing and cost constraints) driver for any given passenger trip request and this kind of objective functions are commonly used in synchronization problem of on-demand and transit traffic. This objective function is utilised in (Kumar & Khani, 2021; Stiglic et al., 2018).

Modelling approach: The most commonly adopted modelling approaches in the consulted literature can be grouped into two categories namely mathematical programming based and rolling horizon based. For example, under the mathematical programming category, (T. Liu & Ceder, 2018) introduced Bi-level programming approaches to solve the considered optimization problem. Non-linear programming (Gkiotsalitis et al., 2022), linear programming (Kumar & Khani, 2021; Levin et al., 2019; Stiglic et al., 2018; B. Sun et al., 2019), quadratic programming (L. Wu et al., 2020), dynamic programming (Gkiotsalitis et al., 2022) and stochastic models (Jia et al., 2020; Lu et al., 2020; Luo et al., 2021; B. Sun et al., 2019) are other commonly used formulations and under rolling horizon category, (Kumar & Khani, 2021; Levin et al., 2019) introduced rolling horizon based scheme for a linear programming problem.

4.4.3 Optimization methods

Multiple researchers have used mathematical programming solvers to handle the synchronization of shared- and on-demand mobility with public transit modes. For example, researchers in (Levin et al., 2019) used linear programming as an optimization method to optimize the integration of shared autonomous vehicle traffic with transit, in (L. Wu et al., 2020), authors have used sequential quadratic programming in order to optimize the synchronization of shared bike network with transit feeder traffic. Mixed-integer programming has been extensively used in the literature (Auad-Perez & Van Hentenryck, 2022; B. Sun et al., 2019) for the optimization of on-demand traffic and transit synchronization. In order to solve the fast/last mile traffic problem authors (Kumar & Khani, 2021) used a rolling horizon strategy coupled with a linear programming solver for solving ridesharing matching.

In addition, we discovered that heuristic-based approaches are commonly employed as optimization strategies. In (Lu et al., 2020), the authors proposed a two-phased optimization model based on a heuristic optimizer with Lagrangian relaxation for optimizing trip planning and operations by integrating a ride-sharing process in short-notice evacuations to incorporate a joint optimization of driver-rider matching and required transfer connections among shared vehicle trips. The bike-sharing rebalancing with interval was formulated as a bi-objective mixed-integer programming model by the authors of (Jia et al., 2020) and solved using multi-objective particle swarm optimization. This MOPSO algorithm belongs to the evolutionary algorithm class.

Apart from above-discussed methods, researchers in (T. Liu & Ceder, 2018) used a bi-objective bi-level model using a deficit step function for public transport timetable synchronization.

4.4.4 Experimentation/test Benchmark

Type of data used: As in the previous category of problems, most of the authors employed synthetic data in their experiments. This is the case with the research conducted by (Costa et al., 2021; Jia et al., 2020, 2020; Lau & Susilawati, 2021; Levin et al., 2019; T. Liu & Ceder, 2018; Y. Liu & Ouyang, 2021; Stiglic et al., 2018; B. Sun et al., 2019; L. Wu et al., 2020). On the other hand, only a few studies, such as (Auad-Perez & Van Hentenryck, 2022; Kumar & Khani, 2021; Lu et al., 2020; Luo et al., 2021) have based their analyses on real data.

Location: Although most of the studies utilised synthetic data, a considerable number of publications based their analyses on real locations (Auad-Perez & Van Hentenryck, 2022; Costa et al., 2021; Kumar & Khani, 2021; Lu et al., 2020; Luo et al., 2021; Stiglic et al., 2018). Some of the locations considered were Chicago, Twin cities, San Fransisco, Sao Paolo, New York, Michigan, Chongquing or Kuala Lumpur. For the rest of the references we looked at based their experimentations on virtual locations (Gkiotsalitis et al., 2022; Jia et al., 2020; Levin et al., 2019; Y. Liu & Ouyang, 2021; L. Wu et al., 2020).

4.4.5 Comparison studies

Comparison methods: Regarding the methods used as the baseline in reviewed studies, it should be mentioned that only two of them include a comparison study of various optimization algorithms or models. Concretely, (B. Sun et al., 2019) and (Jia et al., 2020) considers methods as CPLEX and

NSGA-II, as their baseline algorithms. The other works considered only the comparison againsts different parametrization of their proposals or comparison againsts other synchronize or non-synchronized schemes.

Comparison metrics: total travel time (Kumar & Khani, 2021), minimum waiting time (Kumar & Khani, 2021), total system travel time (Luo et al., 2021), total travel cost (Auad-Perez & Van Hentenryck, 2022; Y. Liu & Ouyang, 2021; Luo et al., 2021), private vehicle kilometer (Lau & Susilawati, 2021) and total travel time and total travel cost are the most common metrics used to estimate performance differences.

4.4.6 Research gaps and assessment of optimization models and techniques

This section aims to discuss the main research gaps we have identified in the reviewed literature.

The first gaps are related to the application scope. We have seen that very few papers addressed the synchronization of shared- and on-demand mobility with public transit in rural scenarios where this synchronization can play a relevant role in providing these locations with a better connection to public transport services.

Another identified gap was related to the lack of studies considering CAVs as the vehicle used to provide shared or on-demand services. Given the high impact that CAVs can have in this synchronization, it is a field that definitely deserves further research.

Furthermore, a shortcoming of the identified literature is the lack of studies based on real demand data which can lead to biased conclusions. Although this category of problems is relatively new and this lack of studies based on real data is probably due to the absence of open data of this kind, it is important that steps are taken towards this direction.

Though we found some comparative studies in the literature, it is worth mentioning that the lack of unified test conditions and test suites can become a hindering issue for the real scientific advance in this category of problems.

4.5 Optimization models and techniques for Dynamic Congestion Pricing

Analogously to the previous two sections, here we aim at discussing and categorizing the literature reviewed related to dynamic congestion pricing. First, section 4.5.1 reviews the application scope of the reviewed papers. Then, section 4.5.2 presents the optimization models usually reported in the literature. These models include the decision variables, constraints, objective function and modelling approaches. Then, section 4.5.3 summarizes the optimization methods typically considered for solving the optimization models previously identified. Afterwards, sections 4.5.4 and 4.5.5 review essential characteristics of the experimental benchmarks (e.g., Data type, Location, Problem Dimension) usually considered to test optimization methods when solving DCP problems. Lastly, section 4.5.64.5.6 highlights a set of gaps reported in the literature regarding the modelling process and optimization of DCP problems.

4.5.1 Analysis of application scope

Context: According to the literature review the majority of papers are focused on urban environments (Cheng et al., 2019, 2021; Chung et al., 2012; Genser & Kouvelas, 2022; Z. Liu et al., 2017; Lv et al., 2022; Salazar et al., 2018). This means that the design of deployment of DCP policies have been prioritized to be developed only in this kind of context. Concerning inter-urban contexts, we have identified only one paper, which expands the scope of DCP to consider multiple urban environments (He et al., 2017; Y. Zhang et al., 2019). Similar to inter-urban contexts, the literature focused on DCP schemes for metropolitan is rather scarce. In particular, to the best of our knowledge, only the study (Luo, 2019) approached DCP policies in peri-urban contexts.

CAVs scenarios: the literature is mostly directed toward scenarios where the traffic is composed of only conventional vehicles and mixed traffic. Specifically, the works of (Cheng et al., 2017, 2019, 2021; Chung et al., 2012; de Palma & Lindsey, 2011; Genser & Kouvelas, 2022; He et al., 2017; Z. Liu et al., 2017; Luo, 2019; Lv et al., 2022; Y. Zhang et al., 2019) studied the different DCP policies that applied to conventional cars; meanwhile, (Salazar et al., 2018) prosed a pricing policy that affects both conventional vehicles and CAVs.

4.5.2 Optimization models

Decision variables: the most common decision variables that we can find in the literature are related to the so-call toll functions. First, we found the distance-toll function which is a continuous nonlinear function that maps the price of a given congestion toll with the travel distance of cars. Some representative research articles that have considered this function are the cases of (Cheng et al., 2019, 2021; Z. Liu et al., 2017). Another common decision variable is the congestion charge rate, which is a fixed or variable congestion fee with the daily charge for driving entering specific congestion charge zones (Cheng et al., 2019).

Based on different assumptions, the congestion charge rate can be differentiated into the first-best tolling and the second-best tolling. The former tolls every arc in the network; while the latter is under the assumption that only a subset of the arcs is tolled (Chung et al., 2012). This second case, congestion charge rate at arc level, is the approach most commonly considered in the consulted literature (Chung et al., 2012; He et al., 2017; Lv et al., 2022; Salazar et al., 2018; Y. Zhang et al., 2019).

Lastly, another relevant variable is the regional time-varying pricing function (Genser & Kouvelas, 2022). Under this decision variable, the price of tolls is higher when the levels of congestion are also high, which is also related to the time of the day (rush hours or not),

Constraints: According to the literature review, there are common constraints imposed for the optimization of DCP problems. Firstly, we can highlight flow dynamics, propagation and conservation constraints (Cheng et al., 2019; Salazar et al., 2018). This constraint, with its variants, is focused on fixing boundaries (min or max) for the road travel times and path flows when optimizing the price of DCP policies. The other relevant constraint typically used is dynamic user equilibrium (Chung et al., 2012) and Stochastic user equilibriums (Cheng et al., 2021, 2021; Z. Liu et al., 2017).

Objective functions: as part of the formulation of optimization models, objective functions are another relevant element to be considered. We have identified three types of objective functions that are representative of the state-of-the-art. Firstly, the total revenue that is a function where the aim is to get as much as possible revenue from a particular DCP policy implemented. Within this type of objective function, we identified the research studies of (He et al., 2017; Lv et al., 2022; Y. Zhang et al., 2019). Secondly, other authors have considered total travel cost or travel time as the objective function, where the objective is to minimize these functions(Cheng et al., 2019, 2021; He et al., 2017; Z. Liu et al., 2017; Lv et al., 2022). The third category of objective functions groups variables that minimize the average delay of trips through DCP (Chung et al., 2012) and decrease the operational costs of a given DCP policy (Salazar et al., 2018). We must say that this last category is less representative in the reviewed literature.

Modelling approach: Within the consulted literature, we have identified a predominant modelling approach, that is, mathematical programming. Within it, the most typical modelling approaches are presented as follows. (Cheng et al., 2019; Chung et al., 2012; Z. Liu et al., 2017; Lv et al., 2022) proposed bi-level programming approaches to model the optimization of DCP policies, as well as non-linear programming and quadratic programming, such as the cases of (Luo, 2019; Salazar et al., 2018).

4.5.3 Optimization methods

The most relevant optimization methods identified in the literature can be classified as heuristic-based and machine learning-based. Specifically, we can find the approach proposed by (Cheng et al., 2019), where the authors introduced an Artificial Bee Colony method integrated with a Self-adaptive gradient projection algorithm. Their aim was to optimize a DCP problem with the consideration of the actual travel distance and time delay in a dynamic network. This bio-inspired approach is based on the intelligent foraging behaviour of the honey bee swarm, which was proposed by Derviş Karaboğa in 2005. This Bee Colony-based approach was also studied by (Z. Liu et al., 2017). In this case, the authors designed a two-phase Artificial Bee Colony algorithm for nonlinear distance-based congestion pricing in a network considering stochastic day-to-day dynamics.

Other authors have also used meta-heuristics techniques for solving DCP optimization problems. For instance, (Chung et al., 2012) developed a Particle swarm optimization model to optimize congestion pricing problems when flows correspond to dynamic user equilibrium on the network of interest. On the other hand, (Cheng et al., 2019) designed a tested a Metaheuristic approach based on the whale optimization algorithm (WOA). The authors' objective was to deal with the optimal congestion pricing problem that considers day-to-day evolutionary flow dynamics.

Lastly, other relevant optimization methods reported in the reviewed literature are the studies of (Genser & Kouvelas, 2022) and (Luo, 2019). The former authors used real-time dynamic pricing's influence and predicts pricing functions to aim for a system optimal traffic distribution by means of Linear Rolling Horizon Optimization and Multi-layer neural network. In the case of the latter authors, they used Bayesian optimization to address the two technical challenges arising from the representation of system dynamics and the optimization for congestion price mechanisms. The authors highlighted that this optimization approach can potentially be extended to solve large-scale congestion pricing problems with unobservable states.

4.5.4 Experimentation/test Benchmark

Data type used: The first element is the type of data used to evaluate the optimization of DCP problems. According to the literature review, the majority of authors tend to use synthetic traffic data due to common issues in finding public data repositories that contribute to the definition and consolidation of benchmarks in the area. We stand out the studies carried out by (Cheng et al., 2019, 2021; Chung et al., 2012; Genser & Kouvelas, 2022; Z. Liu et al., 2017; Luo, 2019; Lv et al., 2022; Salazar et al., 2018), have made use of such a synthetic data. On the other hand, only a few authors have included in their studies real data. That is the case of (He et al., 2017; Y. Zhang et al., 2019).

Location: Based on the results obtained in the literature review, only a small set of papers define the location where their study took place (e.g., Zurich, Manhattan, Maryland, Houston, Texas) (Genser & Kouvelas, 2022; He et al., 2017; Salazar et al., 2018; Y. Zhang et al., 2019). The rest of the references did not base their studies on a real transport network but on a synthetic one (Cheng et al., 2019, 2021; Chung et al., 2012; Z. Liu et al., 2017; Luo, 2019; Lv et al., 2022; Y. Zhang et al., 2019).

Problem dimension: In this regard, the majority of papers consulted were based on a complete network analysis (Cheng et al., 2019, 2021; Genser & Kouvelas, 2022; Z. Liu et al., 2017; Luo, 2019; Lv et al., 2022; Salazar et al., 2018); meanwhile, the intersection and corridor levels were the problem dimension less studied in the literature (Chung et al., 2012; He et al., 2017; Y. Zhang et al., 2019).

4.5.5 Comparison studies

Comparison method: The comparison of methods can be grouped into no comparison at all, self-comparison (different variants of the same method are compared among them) and baseline algorithm comparison (comparisons made against other algorithms different to the one proposed). According to specialized literature, the specific methods of comparisons fall in the categories of probabilistic, meta-heuristics, statistical learning, and simulation models, among others. (Chung et al., 2012) made comparisons against simulated annealing, which is a probabilistic technique for approximating the global optimum of a given function that in this case is the optimal value for the operation of a given DCP policy. (Luo, 2019) set a baseline that included a regression model, which is a simple method to make the comparison when optimizing DCP policies in real-world scenarios. Diversely, other authors have defined baseline with only simulation models. That is the case of the work by (Salazar et al., 2018), where the authors compared an isolated Autonomous Mobility-on-Demand (AMoD) system to an intermodal AMoD system under a pricing scheme. (Lv et al., 2022) introduced a programming approach under stochastic and fuzzy uncertainties (BLP-SF) for a toll scheme design with the considerations of the externalities of vehicular emission and road pricing policy. The baseline to compare this proposal was a User Equilibrium model and inexact minimum emission model.

Comparison metrics: the most relevant metrics we can highlight are the total system travel time (Cheng et al., 2019), total travel cost (Chung et al., 2012; Luo, 2019), total travel time and costs (Salazar et al., 2018), emissions and travel time (Lv et al., 2022), travel times and toll revenue (He et al., 2017), and speed, flows and toll revenues (Y. Zhang et al., 2019).

4.5.6 Research gaps and assessment of optimization models and techniques

This section aims to discuss the main research gaps we have identified in the reviewed literature. The first gap identified concerns the modelling of the problem. Most of the articles reviewed are based on single-objective models. However, DCP, like many other real problems, should consider the optimisation of various objectives (e.g. operational costs, revenue, environmental impact, system performance, etc.) to ensure a more adequate evaluation and implementation of these policies.

Another gap identified is the lack of studies based on realistic scenarios and use of real data, so the conclusions that can be drawn from such studies may be highly biased. The latter is mainly due to the lack of open data of this type, but new studies must move towards this direction.

The last gap that we have identified is the absence of large-scale applications in the literature. In this sense, parallel computing may play a relevant role due to the requirement for short computational times in large-scale, real-time, applications. The distributed and parallel computing approach, which introduces significant improvements in computing performance, is recognized as one of the most efficient means of large-scale computing. For this reason, this can be a promising research trend in the coming years.

5 Description of selected optimization problems

The objective of this section is to broadly define which optimization problems we will potentially focus on in the next WP5 tasks. To do so, we have based ourselves on the literature reviewed and analyzed in Section 3 and on the priorities defined by the different case studies in Deliverable D1.1.

5.1 Coupled traffic signal and route planning optimization for CAVs

According to TANGENT's deliverable D1.1 "Multi-actor co-creation strategies for each case study", many of the objectives of the case studies are oriented to the reduction of congestion and pollution, the optimization of the transportation network and the preparation for the next generation of traffic management systems, as we can see below:

- Rennes' related objectives: reduce congestion, reduce pollution.
- Lisbon's related objectives: reduce congestion, reduce pollution
- Great Manchester's related objectives: reduce accidents, reduce congestion, reduce pollution, align with next-generation traffic management system procurement, improving journey time reliability.
- Athens' related objectives: reducing congestion, reducing pollution, real-time traffic management services

Given that one of the main aims of TANGENT is to develop new tools for traffic management of future mobility scenarios, as we have commented in Section 3.1, in the coming decades, CAVs can be one of the main assets to deal with the objectives mentioned above (Skabardonis, 2020). As we also stated in previous sections, one of the main advances for coordinated traffic management that CAVs will bring is Signal Vehicle Coupled Control which aims to improve the traffic control performance by leveraging the exchange of information in real-time between signals and vehicles, and the simultaneous optimization of signals timing/phases and CAVs trajectories and/or routes (Guo, Li, and (Jeff) Ban 2019), to enhance the performance of the whole traffic network.

However, as we described in Section 4.3.6, the literature proposed to date in this area still has several gaps:

- Most of the literature considered a single objective for the optimization purpose but inherently the SVCC problem is multi-objective in nature.
- Most of the studies published so far are conducted under a 100% CAV scenario or a mixed traffic scenario with a high penetration rate of CAVs.
- Only a few studies focus on the optimization of SVCC at the corridor or network level.

Having said this, the problem that we aim to address regarding SVCC in the coming WP5 tasks is the couple optimization (considering multiple objectives) of traffic signal control and CAVs schedules and routes at corridor level (at least) and under a mixed traffic scenario.

5.2 Optimization of integration of DRT systems with public transit modes

Following the content of Deliverable D1.1 "Multi-actor co-creation strategies for each case study", one of the most repeated objectives among the use cases considered in TANGENT is to increase the use of public transport. In particular, Rennes, Greater Manchester and Lisbon consider it, in one way or another, among their objectives, as we can see below:

- Rennes' directly related objectives: increase public transport, cycling and walking

- Lisbon's directly related objectives: increase of public transport use
- Great Manchester's directly related objectives: increase sustainable transport uptake, increase in bus/metrolink patronage

Furthermore, the increase in public transport used is indirectly related to other objectives as we can see below:

- Rennes' indirectly related objectives: reduce congestion, reduce pollution, decrease single-occupant trips
- Lisbon's indirectly related objectives: reduce congestion, reduce pollution
- Great Manchester's indirectly related objectives: multimodal assistance mobility, reduce accidents, reducing pollution, reducing congestion, improving journey times across modes

As we commented in Section 3.2, one of the main barriers to increasing the use of public transport in cities is the first/last mile problem, especially in areas that are not densely populated and/or where public transport service is infrequent, as it is usually the case of new districts in urban fringes. As also mentioned above, emerging modes of mobility, such as shared mobility or on-demand mobility present an excellent opportunity to address the first/last mile problem, as they have characteristics that are well suited to act as feeders or collectors of public transport. In that sense, Demand Responsive Transport and specifically, its operational variations such as Responsive Feeder Transit and Responsive Collector Transit (B. Sun et al., 2018; Z. Wang, Yu, Hao, Tang, et al., 2020), have shown better manoeuvrability and flexibility, especially for low-density bus travelling regions or for disadvantaged groups, including the aged, children, and the disabled, compared with the fixed-route transit (FRT) (Z. Wang et al., 2021). However, the deployment of these services is still low because of the complex balance between operating costs and service quality(Z. Wang et al., 2021).

Having said this, the main motivation behind selecting synchronization of DRT with public transport as one of the optimization problems to be addressed in upcoming WP5 tasks is two-fold: on the one hand, to contribute to solving the first/last mile problem in public transport, and on the other hand, to improve the efficiency and performance of responsive feeder/collector transit services to make them more viable.

However, the literature proposed to date in this area has major problems (Z. Wang et al., 2021; Z. Wang, Yu, Hao, Chen, et al., 2020):

- Most of the studies consider independent optimisation of running routes (that decides which passengers can be picked up), and departure times even if they are interlinked.
- Only a few studies address the time-dependant travel times. Instead, they consider fixed vehicle speeds which is non-realistic in most urban scenarios.
- Some assumptions related to vehicle fleet are inconsistent with reality as the homogeneous fleet of vehicles and unlimited capacity.

With these ideas in mind, the problem to be addressed in the next stages of WP5 is the joint optimisation of the running route and the scheduling (departure times) of Responsive Feeder Transit and Responsive Collector Transit systems considering mixed demand (both real-time and reserved demand), with time-dependent travel times and with multiple vehicle types.

5.3 Synchronization of Public Transport and Traffic control

As described in the previous section, one of the most frequent objectives among the TANGENT case studies is to increase the use of public transport. As we also discussed in the previous section, one of the main barriers to this increased use of public transport was the first/last mile problem. However, this is not the only problem. Another important barrier limiting a higher use of public transport is travel time, mainly for surface public transport, such as buses, trams or high occupancy vehicles, as they are highly dependent on congestion levels and traffic lights (Bhouri et al., 2015). In this sense, some of the measures applied are the use of exclusive lanes for public transport, urban tolls, redirection of private car traffic to roads with less public transport traffic or the prioritisation of public transport at intersections (Bhouri et al., 2015). The latter measure has shown to be very effective, as it can improve travel times by up to 40% on average (Bhouri et al., 2015).

On the other hand, the capacity and reliability of public transport also have a high impact on the satisfaction and therefore the use of public transport(Cantwell et al., 2009; Cats & Jenelius, 2018). The capacity of a public transport line, measured by the number of passengers it can carry in a given time interval, is given by the frequency and capacity of the vehicles associated with it (Cats & Glück, 2019). The design of a line's capacity has a very important impact as it affects both the route choices of passengers and the operating costs of service providers. However, this process is currently done on the basis of local experience and expert judgement.

Although there is a wide variety of literature related to the optimisation of public transport optimisation (Desaulniers & Hickman, 2007; Ibarra-Rojas et al., 2015), it still has important shortcomings:

- Most of the studies focusing on the optimisation of line capacity in public transport have been based on static transit models.
- The articles published so far dealing with the optimisation of public transport line capacity do not consider the impact it may have on traffic.
- Literature studies address the prioritisation of public transport at signalised intersections and the optimisation of line capacity independently although their interrelationship can have a major impact on the reliability and quality of public transport.

Thus, the optimisation problem to be addressed in the next phases of WP5 is the joint optimisation of the capacity (frequency and size of allocated vehicles) of public transport lines and the prioritisation of public transport at signalised intersections based on dynamic transit assignment models.

5.4 Optimization of Dynamic Congestion Pricing schemes

According to the content of Deliverable D1.1 "Multi-actor co-creation strategies for each case study", apart from the increase in public transport use, many of the main objectives for the four TANGENT case studies are directly related to the reduction of the use of private cars:

- Rennes directly related objectives: Decrease single-occupant trips, Reduce congestion
- Lisbon directly related objectives: Reduced car mileage while searching for parking areas, Reduce congestion
- Great Manchester directly related objectives: Reduce accidents, Reduce congestion
- Athens directly related objectives: Reducing Congestion

Apart from this, another objective present in all case studies that is indirectly related to the reduction of the use of private cars is reducing pollution.

As we commented above in Section 3.3, one of the most promising and effective policies to reduce the use of the private car in urban areas, and also increase the use of public transport, is DCP (Saharan et al., 2020). As we also mentioned in Section 3.3, among the main benefits of DCP we can find the reduction of traffic on specific roads, the maintenance of average speed, the promotion of carpooling and public transportation, the restriction of a particular type of vehicles, the restriction of traffic at specific times and on specific occasions, the generation of revenue, and the balance of cost between payer and payee.

However, as we pointed out in Section 4.5.6, the literature proposed to date in this area has important shortcomings, which are listed below:

- Most of the current DCP schemes are based on single-objective models.
- Only a few papers address large-scale applications of DCP schemes because of their computational complexity.

With these ideas in mind, the problem to be addressed in the next stages of WP5 is the optimization of DCP schemes using a multi-objective and within-day approach. Furthermore, in order to deal with the computational complexity of large-scale applications of DCP, we will make use of model-based optimization and parallel computing.

6 Negotiation and arbitration models for Transport Network Management

6.1 Integrated decision-making in Transport Network Management

Designing and operating an urban transportation system is a complex process that must consider a variety of factors including economic, environmental, and socio-political concerns. The heterogeneity of transport network components lies unavoidably outside the realms of responsibility of various stakeholders who are defined as ‘any individual or group of individuals that is influenced by or can influence the achievement of the organization's objectives’ (Freeman & McVea, 2001). As a result, it is common to find several private and public stakeholders involved in the design and management of urban transportation networks, each with their own objectives and priorities that should be respected (Mardani et al., 2015).

Involving stakeholders in the decision-making process instead of following a “top-down” approach has proven benefits for the multiple components that constitute the urban transport network. In the planning of transport network systems and operations, addressing the stakeholder needs is recognized as a critical success factor, enabling the timely foresight of potential issues. In transport network management and operations, similar benefits have given rise to formal participatory processes between stakeholders. For instance, the U.S. federal transportation legislation for transport network management, Moving Ahead for Progress in the 21st Century Act (MAP-21), has established cooperative decision-making processes for coordinating transportation operations among state and local agencies, recognizing that “interagency and interjurisdictional collaboration is critical for effective regional transportation management” (Meyer & Engineers, 2016). Different examples across the United States include Philadelphia, where 35 regional stakeholders come together to develop a consensus on incident management and ITS systems and Atlanta, where the Regional Transit Committee formed by representatives of operators and political jurisdictions provides input on regional transit planning, funding, and governance, and operation coordination. Similar considerations are also discussed in the urban freight policy development literature, where it is suggested that stakeholder participation and consensus can lead to better prediction of ex-post stakeholder responses, foster trust and cohesion between the involved entities and maximize the quality of decision-making (Knoppen et al., 2021).

In parallel though, the collaboration between the different stakeholders is far from being seamless. The literature suggests that the pre-established interests, power imbalances, conflict between private and public actors, institutional “lock-ins”, interest to defend the status-quo and different professional backgrounds of stakeholders can result in communication issues and in a difficulty in reaching consensus (Hrelja et al., 2020). For a further analysis of the problems that may arise at the interconnection of transportation actors, institutions and work processes, the interested reader is referred to the recent review of (Hrelja et al., 2020). In an effort to address these issues, numerous decision support systems have been proposed to help decision-makers deal with circumstances where there are numerous potential solutions to a problem and none of them is objectively better than the others so that the decision-makers' preferences need to be considered to choose between them (Walling & Vaneeckhaute, 2020).

The rest of this section is structured as follows. In Section 6.2 different consensus definitions are discussed, distinguishing between a “hard” and “soft” interpretation of consensus and examining ways to measure it. In Section 6.3.1 we are presenting traditional approaches of selecting the optimal solution when stakeholder preference focusing on Multi-criteria Decision-making techniques and preference-based Evolutionary Algorithms, after briefly considering approaches based on the Cost-Benefit Analysis family of methods. Finally, in Section 6.3.2 we are discussing state-of-the-art decision-making approaches based on the principles of Agent-Based Modelling, focusing on Agent-Based Negotiations & Agent-Based Social Dynamics.

6.2 Hard vs. Soft Consensus

The notion of consensus, although it occurs quite often when decision-making involving many different stakeholders is required, it does not have a clear definition. The analysis to follow considers two aspects of consensus: hard and soft consensus.

Consensus is associated with a group's agreement level nuancing that group members have a common understanding of the issue at hand. Assuming that the phrase “group members” implies “all group members”, the definition gives rise to the notion of hard consensus, i.e., a complete and unanimous agreement (Kacprzyk & Fedrizzi, 1989). Unanimity, on the other hand, can be difficult (or unnecessary) to attain, especially with vast and diverse groups of decision-makers in real-world contexts (B. Zhang et al., 2019). As a result, a complete and unanimous agreement under any setting is very rare in practice (Herrera-Viedma et al., 2014).

Responding to the rigidity of the hard consensus paradigm, soft consensus describes those conditions that partial agreements between stakeholders might also lead to a consensus while putting more emphasis on the way that the consensus is reached. (Ness & Hoffman, 1998) capture both dimensions in their definition, where, the consensus is “a decision that has been reached when most members of the team agree on a clear option and the few who oppose it think they have had a reasonable opportunity to influence that choice. All team members agree to support the decision.” Soft consensus metrics are extensively employed and it has been suggested that they are more capable of reflecting human perceptions of what constitutes consensus (Herrera-Viedma et al., 2014).

When consensus is no longer associated with complete opinion unanimity, measuring it is no longer straightforward in a group decision-making setting. Generally, two approaches have been identified in the literature (Ben-Arieh & Easton, 2007).

In cases where the opinion of participants is documented in “one-shot”, the consensus is often a calculated metric stemming from the aggregation of individual opinions into a collective one. In this case, consensus refers to a mathematical property of the aggregated opinions such as the point that minimizes the dissimilarity between participants’ opinions or their weighted average (Ben-Arieh & Easton, 2007). The theoretical foundations of aggregating individual preferences into a collective decision or social welfare have been investigated by social choice theory, which is concerned with how to translate the preferences of individuals into the preferences of a group (Kangas et al., 2006). In this case, stakeholders’ preferences are typically represented by preference orderings (where preferences are included in an ordered vector of alternatives from best to worst), utility functions mapping outcomes to utility values and fuzzy, multiplicative or linguistic preference relations that characterize the relative importance of outcomes (Herrera-Viedma et al., 2014). Most of the Multi-Criteria Decision-making (MCDM) Approaches that will be presented in Section 6.1.2 also fall under this category. It is important to consider though that combining different stakeholders' choices could result in inconsistency in decision-making and, more importantly, it might not fully capture stakeholders' aspirations (Le Pira, Inturri, Ignaccolo, Pluchino, et al., 2017). Indeed, the aggregated opinion, in this case, might very well be an opinion that no one explicitly holds.

In contrast, in cases where stakeholders are interactively involved, i.e., they are expected to exchange opinions and converge towards a final, shared decision, consensus refers either to the quality of the final solution, or it can be a way of directing the consensus process until individuals reach high levels o of agreements (Ben-Arieh & Easton, 2007). In this case, consensus measurement might include formal metrics of opinion convergence such as the degree of uncertainty around a point estimate, decreases in the variance of group responses, the proportion of participants agreeing to a certain solution etc. (Diamond et al., 2014). This type of consensus acknowledges that interaction between stakeholders can lead to exchanges of opinions, which can lead to a shared decision supported by all parties (Ben-Arieh & Easton, 2007).

#	Category	Dimensions Captured	Definition of consensus	Metrics
1	Hard Consensus	Final degree of agreement	Complete and unanimous agreement	Percentage of DMs agreeing with the final solution
2	"One-shot" soft consensus	Final degree of agreement	Partial agreement	Preference orderings, utility functions, preference relations and others
3	Interactive soft consensus	Final degree & Dynamics of agreement	Partial agreement	Uncertainty around a point estimate, decreases of group responses variance, proportion of participants agreeing to a certain solution

Table 1: Overview of Consensus Definitions

6.3 Selecting the best alternative

We begin this chapter by identifying the perimeter of a decision-making problem, and defining its key components and actors. Decision-making is a process of choosing from possible courses of action in order to attain goals and objectives (Forman & Selly, 2001). Urban traffic management offers us a typical example of a transport-related decision-making problem, since it entails a continuous decision process of coordination of all the individual elements (traffic signals, arterial roads, traffic, parking) and the interrelated components of urban transport (private and public transit means, pedestrians, etc.) (Boltze & Tuan, 2016). For this coordination to be successful, it must be the result of conscious stakeholder intentions of "goals". In the case of urban traffic management, such (higher) goals typically include a combination of increasing travel (operational and economic) efficiency and safety, protecting the environment etc., and they usually come down to more specific, preferably quantitative, objectives. For instance, goals related to travel efficiency can be translated into specific objectives of strengthening the capacity and productivity of transport supply, while safety and environmental considerations might be articulated into objectives such as limiting the number and severity of accidents and reducing the consumption of natural resources and their associated emissions respectively (Boltze & Tuan, 2016).

In a participatory, bottom-up decision-making context, decision-makers represent the problem's stakeholders, identified as the "individuals or groups who have an interest or some aspect of rights or ownership in the project, and can contribute to, or be impacted by, its outcomes" (Bourne & Walker, 2005). In the context of urban traffic management stakeholders usually involve various levels of government and authorities, the public and private and public service providers and operators. Each individual stakeholder is also embedded into a distinct social role and belief system, resulting in different priorities of the system's objectives. As a result, while all stakeholders perceive more or less the same range of goals and objectives, their priorities and personal agendas result in weighting them differently (Boltze & Tuan, 2016).

The fusion of individual beliefs into a collective, consensus-based group opinion will lead to the identification of the characteristics of the optimal solution and a selection of the alternative possessing the most fitting attributes for attaining the stakeholder's objectives. Returning to our example, in the case of traffic management, decision-makers will choose the optimal configuration of pricing, operating, regulatory and service policies that will lead to the attainment of their collective objectives (Bielli, 1992).

6.3.1 Traditional Practices in Decision-making

While the generic decision-making framework that has been presented above is generally accepted, specificities related to which is the optimal way of engaging stakeholders and documenting their priorities and aggregating opinions into a collective group decision is open to much interpretation. As a result, a wide range of decision-making methods and decision support systems have been proposed in the literature. In this chapter, we present common approaches to selecting the optimal alternative for a given transportation-related problem, focusing on methods belonging to the family of Cost-Benefit Analyses, Multi-Criteria Decision-making and preference-based Evolutionary Algorithms.

6.3.1.1 Cost-benefit Analyses

Within the transportation sector, Cost-Benefit Analysis (CBA) has been for years the most popular tool for evaluating the potential socio-economic impact of decision-making, especially with regard to infrastructure (Yannis et al., 2020). The functioning principle of the CBA is the monetization of potential benefits and costs of all alternatives and the selection of the one offering the best value. Other similar approaches include the Cost-Effectiveness Analysis (CEA) and the Economic-Effects Analysis (EEA) / Economic Impact Analysis (EIA) (Yannis et al., 2020). The use of this family of methods is well documented within the literature and is not the focus of the present review. We note however (Damart & Roy, 2009) who review the applications of the CBA in France and discuss how French institutional entities use the method in order to complement public debates and engage stakeholders regarding transport-related decisions.

Nevertheless, as it has been already discussed, transportation decisions often need to take into consideration the ecological, spatial or social implications of a transport project (Roukouni et al., 2018). The complexity of the issues at hand makes it difficult to value objectively and sufficiently all of the costs benefits and costs (van Wee, 2012), despite the development of CBA variations (namely the Social - Cost-Benefit Analysis - SCBA) explicitly designed to alleviate this issue. An additional concern is that CBA is not able to encompass the different stakeholders' points of view (Roukouni et al., 2018). As a result, its limitations become more apparent when there is a significant difference of opinion among stakeholders on political, socioeconomic, or technological factors (Iniestra & Gutiérrez, 2009).

6.3.1.2 Multi-Criteria Decision-making

Responding to these issues, multi-criteria decision-making has emerged to be one of the most lauded approaches in the evaluation of transportation systems, employed by numerous authorities, academicians, and researchers (Camargo Pérez et al., 2015). Referring, in general, to a family of procedures that assist decision-makers with multiple conflicting objectives and preferences in making decisions related to multi-criteria problems, MCDM is able to deal with high uncertainty and different forms of data and information structure (S. Wang et al., 2022). In transportation, multi-criteria problems are usually "ill-structured", meaning that they are characterized by vaguely formulated complex objectives and high uncertainties (Yannis et al., 2020). The tools capable of handling this problem formulation are commonly referred to as Multi-Attribute Decision-making (MADM) methods. (Sabaei et al., 2015) categorize MADM methods into four categories: Non-compensatory methods, value-based methods, pairwise methods, and outranking methods.

Non-compensatory methods do not allow for trade-offs between the attribute values of different criteria, proceeding to the elimination of the options whose performance is below (or above) a certain threshold. Common non-compensatory methods are the max-min and max-max methods, the conjunctive /disjunctive methods, ordered weighted averaging and others (Kabak & Ervural, 2017).

Value-based methods refer to methods where the valorization vector of stakeholder's rankings for each alternative is transformed into a scalar. The flagship methods of this category are the Simple Additive Weighting method (SAW), TOPSIS and VIKOR. In SAW, the scalar score of a candidate solution is defined as the weighted sum of all attribute values (Afshari et al., 2010). In TOPSIS and VIKOR, the distance between each alternative's individual score is used to determine which solutions are the closest possible to an ideal solution (Beheshti & Rahmani, 2009). TOPSIS applications and methodologies are reviewed by (Zavadskas et al., 2016), while VIKOR applications are reviewed by (Gul et al., 2016) and (Mardani et al., 2015). The development of both techniques has continued well after their introduction in 1981 (TOPSIS) and 1990 (VIKOR), and many extensions and combinations with other methods have been proposed.

Pairwise methods rely on pairwise comparisons of each alternative's attributes, differing from value-based methods in that they follow a distinct methodology of how to combine reciprocal comparisons into a representative group judgement (Kabak & Ervural, 2017) and, at the same time, assess the importance of criteria weights. The most common method is the Analytic Hierarchy Process (AHP) (Emrouznejad & Marra, 2017). The framework has been combined among others with Fuzzy Logic (Fuzzy AHP) (Kahraman & Çebı˙, 2009), Data Envelopment Analysis (DEAHP) (Ramanathan, 2006), SWOT analysis (Abdel-Basset et al., 2018), TOPSIS (Mathew et al., 2020), the Delphi framework (Le Pira, Inturri, Ignaccolo, Pluchino, et al., 2017), Multi-Attribute Utility Theory (MAUT) (Tsamboulas & Kopsacheili, 2003), and others. It has also been extended in the most general form of the Analytic Network Process (ANP), where the decision-making problem is represented as a network of clustered criteria and alternatives (Aragonés-Beltrán et al., 2010). Given its prominence among the different MCDM techniques, AHP is reviewed extensively in the literature. Among the reviews, we highlight (Emrouznejad & Marra, 2017), who trace the development & application field of the AHP by reviewing 8441 papers from 1979 to 2017.

Finally, the outranking methods are based on the elaboration and the exploitation by the decision-makers of an outranking relation between the different alternatives. The leading models in this category are ELECTRE and PROMETHEE, prominent reviews of which include (Govindan & Jepsen, 2016) and (Behzadian et al., 2010).

It should be noted here that the beforementioned list of MCDM methods is not exhaustive, and some methods do not fit this taxonomy. We also make special notice of Multi-Actor, Multi-Criteria Analysis (MAMCA) (Macharis et al., 2009), as a suitable method for evaluating transportation projects as an extension of MCDM methods. This process is unique since it uses a bottom-up approach to define stakeholder objectives, allowing for distinct objectives to be considered for each stakeholder group, and revealing consensus and conflicts of the different decision groups that are involved in the decision-making process. Thus, the main goal of MAMCA decision-making is to find the optimal trade-off between the objectives of the many stakeholders (Janjevic et al., 2019).

When it comes to applications of MCDM methods in transport-related decisions, their history spans more 40-year, starting from the seminal papers of Roy and Hugonnard in 1982 who developed and applied ELECTRE IV for the evaluation of extension proposals for the Paris metro (Roy & Hugonnard, 1982). General recent reviews around transportation include Camargo Pérez et al. (2015) who review multicriteria decision-making applications related to the design and operation of urban passenger network systems. Similarly, (Macharis & Bernardini, 2015) review MCDM application in transport (including freight) project evaluation. In (Mardani et al., 2015), the authors classify MCDM applications in the transport sector by infrastructure type and application area and posit that hybrid and fuzzy extensions of the different frameworks are becoming increasingly dominant within the sector. More recently, (Yannis et al., 2020) reviewed applications of the MCDM methodologies in general transport-related applications and they conclude that the applications refer mostly to the evaluation of transport options (i.e., alternative solutions) rather than distinct transport policies.

In the table that follows, we are presenting the main literature reviews that have been the basis of this chapter. In the "Focus" column, the "Applications" key denotes papers that mainly present the different decision-making problems where MCDM methods have be applied to. On the other hand, papers that focus on the theoretical development of MCDM methods are denoted by the characterisation "Theory". These papers discuss, primarily, the mathematical background and assumptions of MCDM methods, as well as their different extensions, advantages and disadvantages with respects to other methods etc.

Author	Year	Period covered	Reviewed papers	Reviewed Methods	Focus	Application domain	Literature review method
Behzadian et al.	2010	1985-2010	195	PROMETHEE	Applications	Various, including Logistics and Transportation	Not mentioned/other
Camargo Pérez et al.	2015	1982-2014	86	Multiple	Applications	Appraisal of urban passenger transport systems	Systematic literature review (SLR)
Macharis & Bernardini	2015	1985-2012	276	Multiple, focusing on MAMCA	Applications	Appraisal of Transport projects	Not mentioned/other
Mardani et al.	2015	1993-2015	89	Multiple	Applications	Appraisal of Transport Systems	Systematic literature review (SLR)
Govindan & Jepsen	2016	1968-2013	686	ELECTRE	Applications	Various	Systematic literature review (SLR)
Zavadskas et al.	2016	2000-2015	105	TOPSIS	Theory	Various	Not mentioned/other
Gul et al.	2016	2000-2015	343	VIKOR	Applications	Various	Not mentioned/other
Emrouznejad & Marra	2017	1979-2017	8441	AHP	Theory	Various	Data extraction from the ISI WoS academic database. Analysis with a scientometric approach social network analysis (SNA)
Yannis et al.	2020	1982-2019	52	Multiple	Applications	Appraisal of transport projects, policies and transport options	Not mentioned/other

Table 2: Reviewed Literature on MCDM methods

6.3.1.3 Preference-based evolutionary multi-objective optimization

Decision-making problems that involve meeting multiple performance objectives simultaneously can be formulated as Multi-Objective Problems (MOPs). The solution of MOPs usually consists of a cluster of different combination of the decision variables representing different performance trade-offs between criteria (Pareto front) (Purshouse et al., 2014). Multi-objective Evolutionary Algorithms (MOEAs) have proved to be a credible technique for estimating efficiently the Pareto front in MOPs, being able to do so in a single run (S. Wang et al., 2022). Simultaneously, decision-makers are usually interested in the subsection of the Pareto front that corresponds to their preferences. As a result, preference-based evolutionary algorithms for solving the multi-objective optimization problem have emerged, where stakeholder preferences are taken into consideration in identifying the solutions of interest inside the Pareto front. Given that inclusion of multiple conflicting criteria in decision-making is the traditional objective of MCDM, MOEA-MCDM integration is an active area of research in literature (Purshouse et al., 2014).

Depending on which phase of the optimization process the stakeholder's preferences are incorporated, preference-based Multi-objective Evolutionary Algorithms can be classified into a priori, interactive, or posteriori algorithms (H. Wang et al., 2017).

In a priori algorithms, the preferences of the decision-makers are specified before the optimization process. In this case, the aspiration of decision-makers (usually in terms of a reference point or a subregion inside the solution space), guides the solution process towards the preferred region of the

Pareto frontier. Common algorithms employed in similar problems include variations of NSGA-II, PBEA, PSSA, MOPSO and others (Ojha et al., 2019).

In interactive methods, DM preferences are incorporated during the optimization process, allowing for the refinement of preference articulation as decision-makers can specify progressively the appropriate values of the problem's parameters. After each iteration, the decision-maker evaluates the Pareto-optimal solutions at the output of the optimisation algorithm and the responses are utilised in order to improve the Pareto-optimal solutions of the next iteration (H. Wang et al., 2017).

A posteriori algorithms incorporate decision-maker's preferences after the generation of the Pareto-optimal set of solutions, under a Generate First–Choose Later approach. Since stakeholder preference information is included after the identification of the Pareto front, most MOEAs adhere to this category (Messac & Mattson, 2002), with NSGA-II, MOEA/D, GWASF-GA being only three of the most relevant MOEAs for solving this type of problems (Méndez et al., 2020).

In all of the above cases, capturing stakeholders' preferences is usually done through methods where stakeholders specify preferences through utility functions or specific targets values for the different objectives, specify areas of interest in the objective space through the use of reference vectors, or characterize the decision criteria through weights and preference relations (H. Wang et al., 2017). A review of these methodologies can be found in (Rachmawati & Srinivasan, 2006) and (H. Wang et al., 2017). Interestingly, in methods where stakeholder preferences are included a posteriori over the outputs of the multi-objective algorithm, MCDM methods can be used to identify the optimal solution. For instance, in (Méndez et al., 2020), the authors have applied the TOPSIS framework to select the most desirable solution (in this case, a bridge rehabilitation scheme) among the solutions to a budget allocation optimization problem.

Early reviews on Multi-objective Evolutionary Algorithms (MOEAs) incorporating stakeholders' preferences include (Coello, 2000) and (Rachmawati & Srinivasan, 2006). A priori methods have been reviewed by (Branke, 2008), while interactive methods have been reviewed by (Jaszkiewicz & Branke, 2008). (Purshouse et al., 2014) has reviewed all three approaches, while (H. Wang et al., 2017) focus on a posteriori incorporation of stakeholder preferences and selection of the optimal alternative through MCDM methods. More recently (Ojha et al., 2019), have reviewed the state-of-the-art in preference-based multi-objective optimization, discussed preference elicitation methods and presented the key future challenges of the sector.

Author	Year	Focus on	Reviewed methods for incorporating preferences	Preference incorporation
Coello	2000	Theory & Methodology	Goal Attainment, Utility Functions, Objective ranking, Outranking, Fuzzy logic	A priori, interactive, a posteriori
Rachmawati & Srinivasan	2006	Theory & Methodology	Trade-off between objectives, Goal Specification, Objective Ranking, Outranking, Fuzzy Logic, Solution Attributes	A priori, interactive, a posteriori
Branke	2008	Theory & Methodology	Reference point, Trade-offs between objectives, Solution Attributes, Objective ranking	A priori
Jaszkiewicz & Branke	2008	Theory & Methodology	-	Interactive
Purshouse et al.	2014	Applications	Reference point, Objective ranking, Trade-off information, Utility functions	A priori, interactive, a posteriori
H. Wang et al.	2017	Applications	MCDM methods	A posteriori
Ojha et al.	2019	Applications	Objective functions, reference points, utility functions, Objective ranking, trade-offs between objectives	A priori, interactive, a posteriori

Table 3: Reviewed Literature on MCDM preference-based Evolutionary algorithms

6.3.2 Agent-based modelling

In this subsection, we discuss state-of-the-art decision-making approaches based on the principles of Agent-Based Modelling, focusing on Agent-Based Negotiation and Agent-Based Social Dynamics. In this case, the decision-making problem is seen either as an issue of negotiation being autonomous agents (Agent-Based Negotiation), or as a game of influence between agents belonging to a specific social structure (Agent-Based Social Dynamics). Both approaches adhere to the general framework of Agent-Based modelling (ABM).

6.3.2.1 Agent-Based Modelling Generalities

Agent-based modelling (ABM) considers a system as a collection of autonomous decision-making entities (called agents), each of which strives towards its goals by acting according to a set of beliefs (Bonabeau, 2002). The ABM agent lives in an artificial world which he shares with other agents with similar characteristics. By communicating with each other, perceiving and manipulating the state of the world, and learning and adapting their behaviours, the agents are able to succeed in their objectives without having a “success strategy” defined ex-ante (Macal & North, 2005).

ABM is, thus, a natural way to describe a system from the perspective of its constituent units with complex individual behaviours, characterized by non-linearities, path-dependencies, non-markovian behaviours and temporal correlations among others (Bouarfa et al., 2013). For instance, it is more natural to describe how the complex, independent transportation stakeholders negotiate by creating a negotiation instance of autonomous agents than by devising a model that simulates the actual dynamics of their negotiation. That is, when modelling components rather than systems, the structure of the system is not pre-defined and will be defined ex-ante (Maggi & Vallino, 2016).

As a result, ABM allows for the observation and analysis of the emergent phenomena, i.e. events decoupled from the properties of the system’s parts and emerging only from their interaction (Gilbert & Troitzsch, 1999)). A characteristic example of an emergent behaviour from transportation is the shockwaves emerging in a situation of traffic congestion and queueing: their behaviour is not a result of the individual behaviour of the system (the vehicles), but emerges, sometimes counterintuitively, from their interaction (indeed, shockwaves can move in the opposite direction from the traffic congestion that created them) (Bonabeau, 2002). In comparison, in traditional decision-making, aggregating stakeholder preferences without simulating the effects of their simultaneous acting across a given problem limits the capability of these methods to acknowledge and anticipate interaction-triggered emergent phenomena (Choi et al., 2001). Indeed, many traditional decision-making techniques solicit decision-makers either at the very beginning, in order to define their priorities, or at the very end, by providing input to the findings (Macharis & Bernardini, 2015).

Thus, ABM is a potent tool for representing in vitro the complex interactions between actors, as well as the diversity and the inherent variability which characterize the transport systems where heterogeneous stakeholders are in constant deliberation and interaction with each other. (Le Pira, Inturri, Ignaccolo, Pluchino, et al., 2017) proceed in suggesting that ABM can be used to model all decision-making paradigms that involve (or must involve) stakeholder participation and consensus in complex decisions such as transportation policy-making, and note that interaction is already at the basis of methods participatory decision-making methods such as Delphi. (Eshragh et al., 2015) also, suggest that modelling a negotiation between stakeholders through ABM can reduce the complexity of the negotiation space and propose suitable solutions by exploring and filtering the agreement space based on stakeholder preferences while unloading them from time-consuming participatory activities.

Closing this introduction, we quote (Bonabeau, 2002) in saying that ABM is a mindset more than a technology, in the sense that there are many methodologies of creating an interaction game among autonomous stakeholders. In the rest of this review, we proceed in identifying two approaches of particular interest: Agent-Based Negotiation and Agent-Based Social Dynamics. The interested reader is also referred to the comprehensive introduction to Agent-Based Models by (Macal & North, 2005)

6.3.2.2 Agent-Based, automated negotiations.

Automated negotiation is a distributed search in the space of potential agreements by negotiating autonomous agents (Jennings et al., 2001). Based on the intuition that negotiation is one of the most common means for resolving conflicting situations in social interactions (Van Kleef et al., 2006), an agent-based negotiation tries to recreate a complete negotiation instance without the in-person participation of human decision-makers.

An automated negotiation consists of three main components: a negotiation protocol, a negotiation domain, and a negotiation strategy. The negotiation protocol is a collection of rules that governs how agents engage with one another. It also defines which agents can participate in the negotiation round, the rules of concluding a round, as well as the permitted actions (Eshragh et al., 2015). The negotiation domain refers to the issues at the negotiation table, with agents negotiating over multiple issues (i.e. the frequency, route and price of a public transit line) or a single issue.

The negotiation strategy refers to the set of rules that determine the agent's actions for a given negotiation states. The strategies of the agents include game theoretic equilibrium strategies, heuristic approaches and argumentation-based approaches (Jennings et al., 2001). In game-theoretic techniques, each agent is endowed with a strategy which enables him to propose the most rational bid in every round (MacKenzie & DaSilva, 2006). Heuristic approaches on the other hand search for approximate, suboptimal but satisfactory solutions but are free from a wide range of constraints that game-theoretic approaches assume, among others, the need for perfect agent rationality, difficulties in the inclusion of more than two agents, knowledge of opponent's agreement space (Eshragh et al., 2015). Argumentation based approaches posit a somewhat different conceptual framework, where agents exchange logical arguments for persuading the other party (Kiruthika et al., 2020). Reviews on argumentation-based techniques include those by (Maudet et al., 2007) and (Dimopoulos & Moraitis, 2014)

The negotiation strategy can be further analysed into three distinct models: a bidding strategy, a model of the opponent and an acceptance strategy (Bakker et al., 2019). The bidding strategy defines the content and time of an offer. Most common bidding strategies include time-dependent, resource-dependent or behaviour dependent tactics (Vente et al., 2020).

The opponent model observes the opponent's offers and counter-offers in order to develop an understanding of the priorities of the other negotiation parties in terms of which offers are more likely to be accepted. The most common approach is currently Bayesian learning, but other methods such as non-linear regression, kernel density estimates, neural networks, polynomial interpolation and genetic algorithms have been proposed (Vente et al., 2020). Different opponent models are reviewed by (Baarslag et al., 2013) and (Albrecht & Stone, 2018).

The acceptance model determines the rules of whether (and when) the incoming offer should be accepted based on time (close to the negotiation deadline or not) or utility and is reviewed by (Baarslag et al., 2013). Aside from the topic-specific literature reviews that we have already mentioned, recent general literature reviews on the topic include (Fukuta et al., 2016), (Vente et al., 2020), (Kiruthika et al., 2020). We also note the seminal literature reviews of (Kraus, 1997) and (Jennings et al., 2001).

Automated negotiations remain underused in consensus-reaching applications between transport stakeholders. It has however been applied successfully in the field of environmental resources management which presents similarities to our case. Indeed, managing environmental resources entails taking decisions on complicated, multi-issue and high-risk subjects, while accommodating the perspective of multiple, heterogeneous and influential stakeholders exhibiting different priorities

(Eshragh et al., 2015). We note (Eshragh et al., 2015) who review automated negotiation applications in environmental resource management, where decision-making challenges present structural similarities to transportation problems (multiple stakeholders representing public or private entities with heterogenous goals, a single project version to be implemented under budgetary constraints, strong environmental considerations and others).

6.3.2.3 Combining automated negotiation with multi-agent-reinforcement learning

When combining the framework of Agent-Based Negotiations discussed above with Reinforcement Learning (RL), the learning process of the interacting agents becomes iterative: agents perform actions, reach the next environmental state and receive a reward, i.e., the motivational signals that reward certain outcomes and punish others (Canese et al., 2021). The repetition of the process results in a mapping (policy) of the actions at any given state that result in the highest rewards. Agents can also learn cooperative actions in order to collectively solve problems. In these games, the preferences of agents are commonly mapped through a linear or non-linear utility function. Depending on the type of reward, Multi-Agent RL algorithms can be classified as fully cooperative (maximizing a single reward for all agents), fully competitive (zero-sum games), and mixed cooperative–competitive (Canese et al., 2021).

In some negotiation applications, MARL algorithms have been used for learning optimal strategies for generating or accepting offers, or for opponent modelling. For example, DQN has been employed for learning the optimal offer acceptance strategy, while Tabular Q-learning has been used for the bidding and for opponent modelling (Sunder et al., 2018). In these cases, the optimal strategy is learned by the participation of many negotiation instances with an opponent. Reinforcement learning has also been employed in modelling negotiation in human language, but these applications lie outside the scope of this review. The interested reader is redirected to (Cao et al., 2015). These techniques have been employed in applications such as the negotiation of contracts (Sunder et al., 2018), allocation negotiations (Georgila et al., 2014) and division of assets between agents under risk, both for single- and multi-issue negotiations (Schmid et al., 2020).

			Negotiation Approach			Agent Structure			Negotiation Structure	
Author	Year	Focuses on	Argumentation Based	Game theory	Heuristic	Bidding Strategy	Opponent Model	Acceptance Strategy	Negotiation protocol	Negotiation Domain
Kraus	1997	Theory		×						
Jennings et al.	2001	Theory	×	×	×					
Maudet et al.	2007	Theory & Applications	×			×	×	×	×	×
Baarslag et al.	2013	Theory & Applications			×					
Dimopoulos & Moraitis	2014	Theory	×			×	×	×	×	×
Baarslag et al.	2015	Theory & Applications			×		×	×		
Eshragh et al.	2015	Applications			×	×	×	×	×	×
Fukuta et al.	2016	Theory & Applications			×	×	×	×	×	×
Kiruthika et al.	2020	Theory & Applications				×	×	×	×	
Vente et al.	2020	Theory			×	×			×	×

Table 4: Reviewed agent-based negotiation aspects by literature review

6.3.2.4 Agent-based opinion dynamics

Opinion dynamics have their roots in social sciences and, in particular, social impact theory (Castellano et al., 2009), which studies the ways individuals are influenced by the opinions of their peers and vice-versa. Recently, agent-based opinion dynamics have been applied in reproducing the decision-making sequence where modelled stakeholders-agents are requested to evaluate policies or rank the importance of objectives (Le Pira, Inturri, Ignaccolo, Pluchino, et al., 2017). In this setting, the autonomous agents are represented as nodes linked together inside a network that recreates the social and institutional positions between real-life stakeholders. The process recreates the opinion exchange flows between the stakeholders (Le Pira, Inturri, Ignaccolo, & Pluchino, 2015). After each round of interaction, the agents influence and get influenced, updating their opinions until a consensus over a shared solution is reached. The consensus, in this case, is commonly defined as the desired degree of opinion overlap, resulting in a collective preference ranking among plan alternatives. Different topologies and communication costs have been examined by recreating the structures used in Delphi models and hierarchies emulating social networks and different power and information distributions (Le Pira, Inturri, Ignaccolo, & Pluchino, 2017).

Agent-based opinion dynamics have been recently applied in modelling opinion exchanges in decision-making activities involving multiple stakeholders. Regarding transportation-related applications, the only example of relevant applications that the authors are aware of comes mainly from the work of le Pira and her collaborators at the University of Catania. Most recently (Marcucci et al., 2017) have also integrated ABM opinion dynamics and Discrete Choice Modelling. In this case, discrete models are used to capture stated preference heterogeneity and generate agent-specific utility functions for urban freight stakeholders (i.e., retailers, transport providers and own account providers) with respect to changes in policy. The ABM model was then employed to recreate and analyse the social dynamics of the participatory decision-making process, resulting in the identification of an urban freight policy supported by the majority of agents. It should be noted though that, at this stage, ABM simulating opinion dynamics seems to be more capable of providing insights for the design of a real-life participatory process (based for example on an MCDM method) than taking over decision-making autonomously. For example, (Le Pira, Inturri, Ignaccolo, & Pluchino, 2017), compared the results of AHP- and Delphi-based field experiments eliciting preferences regarding mobility management strategies and bicycle use with agent-based social dynamics models. They have shown that agent-based modelling can provide insights into the design of a real-life group decision-making process, but they raised doubts about whether they can replace them. Finally, a comprehensive review of the main opinion dynamic models and applications in other fields can be found in (Castellano et al., 2009).

Author	Year	Preference Elicitation Method (individual level)	Consensus Definition	Goal	Comparison of results to other methods
Le Pira et al.	2015	Pairwise comparisons of alternatives	Overlap of individual and collective preference list	Reaching a consensus-based collective opinion in Transport Planning	AHP / PMR
Le Pira, Inturri, Ignaccolo, Pluchino, et al.	2015	Random preferences	Overlap of individual and collective preference list	Modelling stakeholder interaction on different networks	No
Le Pira et al.	(Le Pira et al., 2016)	Random preferences	Complete consensus among stakeholders	Modelling of a public participation process	No
(Le Pira, Inturri, Ignaccolo, Pluchino, et al., 2017)	2017	Pairwise comparisons of alternatives	Overlap of individual and collective preference list	Reaching a consensus-based collective opinion in Transport Planning	AHP/ PMR during a Delphi process
Le Pira, Inturri, Ignaccolo, & Pluchino	2017	Pairwise comparisons of alternatives	Overlap of individual and collective preference list	Modelling of a Delphi process	AHP/PMR during a Delphi process
Marcucci et al.	2017	Individual Utility functions by Discrete choice modelling	Percentage of individuals in majority	Modelling of multilevel stakeholder interaction	No

Table 5: Aspects covered within the reviewed agent-based social dynamics literature

6.4 Guidelines for the development of a consensus-reaching mechanism

In this section, we briefly consider some practical guidelines that delineate the development of a consensus-reaching mechanism, discussing its objective, scope, domain of application, stakeholders, data needs and modelling approach.

6.4.1 Objective

Most transportation optimization procedures may result in a “cloud” of solutions where each solution is composed of different configurations of the multi-objective optimization problem decision variables. Within TANGENT, these solutions are the result of the different possible configurations of the system services and subservices, responsible, among others, for the congestion pricing, the synchronization of transit and traffic, the synchronization of on-demand and transit modes etc. These services are considered to be simultaneously active within the system and their combination leads to the optimal transport network conditions. Since the possibilities of configuring the decision variables within each service have a wide range (e.g., consider the different pricing schemes within the Dynamic Congestion Pricing module to name one), the possible configuration of the multiple decision variables belonging to multiple services give rise to multiple solutions regarding the parametrization of the overall system.

However, few stakeholders would answer that they are interested in a specific configuration of the transport network in itself. Instead, each combination of system parameters should be evaluated by its ability to respond to a number of what we will refer to as “higher objectives”, i.e. specific objectives delineating each stakeholder’s priorities and goals with respect to the functioning of the transport network system. Examples of “higher objectives” can include objectives related to the reduction of GHG emissions and the addressing of similar environmental concerns, objectives reflecting the willingness to decrease congestion levels or increase traffic safety, passenger safety in the case of an extreme event etc. As a result, each possible combination of the system’s parameters is associated with a specific “performance” in a range of “higher objectives”. For example, raising the average speed within the network can be associated with increased performance in relation to congestion-related criteria but decreased performance with respect to an environmental objective that penalises GHG emissions. Thereby, the multitude of possible system parametrizations gives rise to a different “cloud” of solutions containing a quantitative depiction of “higher-objective” performance.

Ideally, this cloud of solutions is Pareto-optimal, meaning that it is not possible to increase performance in one objective (e.g. reduce GHG emissions), without decreasing the performance in a different one (e.g. by reducing average speed). This solution cloud is potentially very large and, therefore, there is a need to select a smaller number of solutions (ideally one) from within it. To do so, the key intuition is that not all higher objectives are equal and the solutions to be selected are those that are best aligned with stakeholders' priorities. In other words, the chosen solution must lead to optimal performance to the objectives that matter the most to stakeholders.
Nevertheless, deciding which objectives are most important when managing transport networks contains strong elements of subjectivity: different stakeholders in transport network management have completely heterogeneous preferences regarding their prioritisation. As a result, the consensus mechanism that will result from Task 5.4 aims to find an unbiased consensus among stakeholders regarding the importance of each objective. A consensus-based optimal combination of “higher objectives” can, then, be traced back to an optimal decision variable configuration for the transport network.

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6.4.2 Levels of Decision-Making

We distinguish three (3) levels at which the consensus-reaching mechanism could be integrated/activated, corresponding to the major types of decision-making and planning: a strategic level, a tactical level and an operational level. Depending on the level of decision-making, the function of the mechanism could be substantially differentiated. For instance, in case the mechanism acts at the strategic level, the consensus could help establish the general priorities of stakeholders regarding the configuration of the network. Conversely, a mechanism acting at the operational level can help establish the short-term, circumstance-specific priorities of stakeholders. Depending on the decision-making level, the granularity of the data/information needed to reach a consensus is significantly different and ranges from information about strategic objectives that are valid for many years to information valid only for the event necessitating the consensus.

6.4.3 Application Domain

The form of the consensus mechanism can vary depending on the application domain.

The first potential area of application of the consensus mechanism is identified in the creation of response plans, aiming at optimizing network behaviour by orchestrating the network's recovery process from minor or major network disruptions. To do so, they trigger actions (i.e., specific configurations of the respective decision variables) related to user information, congestion pricing, synchronisation of transit and traffic and the synchronisation of on-demand and transit modes etc. They can be predefined and triggered by specific network conditions or be defined ad-hoc for the adaptation of the network. In this context, three potential domains where there might be a need for soliciting stakeholder consensus can be identified:

- A consensus related to the triggering mechanism of the response plan: This first instance refers to reaching a consensus about which (or whether) network conditions necessitate the activation of the response plans. In this case, the stake of consensus among stakeholders is on the one hand the metric (e.g., a KPI) or combination of metrics that should be evaluated for deciding and secondly, the corresponding threshold for activating the response plans.
- A consensus related to the content of the response plan: This second instance refers to a possible consensus with regard to the optimal network configuration for attenuating a given disruption. In this second case, the stake of consensus among stakeholders is the optimal parametrization of the network services and subservices through the "tweaking" of the corresponding decision variables.

We finally note that stakeholders might display both network-wide and corridor-specific priorities, a distinction that adds further granularity regarding the domain of application of the consensus mechanism.

6.4.4 Stakeholders

Stakeholders in the decision-making process will correspond to the typical stakeholder groups involved in transport network management decisions, such as users, operators, transport authorities, representatives of the private sector, public institutions and levels of government, and others.

Depending on its institutional role and areas of responsibility, each stakeholder must meet multiple objectives spanning across all decision-making levels. Each objective is associated with one or multiple strategies for achieving them while being limited by various regulatory, economic, and societal constraints. In other words, every stakeholder has preferences, representing trade-offs between different objectives and preferred courses of action. An accurate portrayal of these individual preferences is thus crucial when seeking a consensus among stakeholders.

As we have already mentioned, managing transport networks falls under the responsibility of various, heterogeneous stakeholders, who are in charge of the operation of different components of the transport network. The responsibility areas of each stakeholder are usually well-defined and they usually possess important formal decision-making power within them. For instance, the traffic light signal timings fall under the responsibility of traffic operators, who will be the ultimate judge of whether they need to be reconfigured.

Under this perspective, we identify as critical the stakeholders who have the responsibility to implement or block decisions regarding the parts of the transport network system that falls under their jurisdictions, and/or stakeholders who possess significant expertise and impact on decisions affecting those parts of the network. For example, critical stakeholders concerning changes in public transit offers to include at a minimum the corresponding public transport operator and possibly public transit authorities, local government etc. Critical stakeholders can also be differentiated in relation to the particular characteristics of the issue at hand. For instance, local civil protection agencies might be considered as a key stakeholder in the case of an extreme incident affecting traffic and as a normal-priority stakeholder in the case of minor incidents. This distinction between critical and normal stakeholders should also be reflected in the evaluation of their preferences, with the key intuition being that more important stakeholders must be more influential in the consensus-reaching process.

Finally, to depict the preferences of the stakeholder groups, participation from human decision-makers will be sought. Each stakeholder group will be represented either by one key stakeholder (e.g. the public transit operator of a given city) or by a group of stakeholders (multiple public transit operators operating across different cities).

6.4.5 Data Requirements

We distinguish two data sources at the input of the consensus-reaching mechanism: on the one hand the aforementioned “cloud” of different, Pareto-optimal solutions contains the performance of a range of different decision variable configurations towards the different “higher objectives” and, on the other hand, a quantitative depiction of stakeholders’ preferences.

Ideally, the solutions “cloud” will be the result of the simultaneous optimization of TANGENT services, since the optimization of one service or of sub-groups of services will not lead to a global optimum when all services are simultaneously active. Given that each service is configured through different decision variables, evaluating multiple attributes of the decision variables is equally important.
As a result, a solutions “cloud” containing multiple attributes of multiple services will result in a rich Pareto front, consisting of a sufficiently large number of Pareto-optimal solutions for the stakeholders to choose from. It is noted however that the simultaneous optimization of multiple services can be quite burdensome, demanding the development of an efficient and robust optimization technique. Simultaneously, a fine granularity of the decision variable configurations will also require extensive simulation effort, given that each new attribute requires simulating its effects over the entire transport network.

While the “cloud” of these solutions will be provided by tasks T5.1, T5.2 and T5.3, the consensus-reaching mechanism will provide the framework for collecting, documenting, quantifying and assessing stakeholders’ preferences. The preference data will be represented by utility values, preference relations or rankings or similar structures able to capture stakeholders’ priorities in a quantifiable way.

We also note that the way in which stakeholders interact with the consensus mechanism determines important aspects of how the data is recorded and processed. We distinguish between two cases:

- In the first case, stakeholders are required to “on-the-spot” document their preferences through the consensus mechanism for the near-real-time optimization of aspects of the transport network or the resolution of an incident. In this case, limitations are imposed on the method of collecting stakeholders’ preferences - which cannot, for example, rely, on detailed interviews-, as well as on the extent-duration of the interaction with them - which cannot be effort-consuming.
- In the second case, the stakeholders’ preferences are recorded at an earlier time, which is temporally distant from the consensus-requiring event. In this case, many constraints on the type of interaction with stakeholders are negated, allowing data to be collected over time and result from deep interaction with the stakeholders. It must be ensured however that the collected stakeholders’ preferences are indeed relevant to the specific instance requiring cooperation, whose particularities are not known ex-ante.

Finally, the data output of the mechanism will have the same ontology as the initial “cloud” of solutions, but the solution will be drastically reduced, containing only options that are compatible with stakeholders’ preferences.

6.4.6 Modelling Strategy

We distinguish two, largely independent, components for the mechanism: a framework for collecting stakeholders’ opinions and a framework for combining them into a consensus-based collective opinion.

Collecting stakeholders’ preferences will be achieved through a structured questionnaire disseminated via various channels. In cases where stakeholders are represented by multiple individuals (e.g., many representatives of the public transport operator), a consensus-based opinion will be sought for reducing the inter-group opinions into a single, representative stakeholder opinion. This process will be achieved using the same consensus-reaching mechanism that will be developed for the higher-level problem of reaching consensus between the different stakeholders, that is, transport authorities, operators, the public etc. The open architecture of the system will also make it possible to add or remove stakeholders if needed.

For combining preferences into a collective, consensus-based preference structure, the application of the methodologies presented in the previous chapter of Section 5 will be explored. The resulting mechanism will be automated to the degree possible, limiting the need for effort-consuming interaction with the stakeholders. Both traditional and state-of-the-art methods will be evaluated. Traditional consensus-reaching methods are well established within the transportation literature but they might fail to capture aspects of human decision-making while being demanding on resources. On the other hand, state-of-the-art agent-based techniques can alleviate these issues, but there are only a handful of applications in transport-related applications.

Comparing the performance of dissimilar objectives also necessitates a mechanism that will establish quantitative performance trade-offs between the criteria and provide a common basis for reaching a decision. For instance, a mechanism that succeeds in the monetization of each criterion fits that description. We will consider whether this trade-off mechanism can be fused with the mechanism of soliciting stakeholders’ opinions. In this case, stakeholders directly provide quantitative valorisations of the different objectives, which are used to decipher both what stakeholders prefer and how much they do so.

7 Software tools for optimization of Transport Network Management

This chapter aims to provide an overview of agnostic software tools that can be used for the optimization of transport network management. Within the main software found in the state-of-the-art, we can group the software tools into two categories, namely, machine learning-oriented like Sequential Model Algorithm Configuration (SMAC), Keras, TensorFlow, TensorFlow Model Optimization, Scikit-learn and optimization oriented like DEAP, PyMoo7 and Nevergrad. Details of these software packages are presented below.

- **Machine Learning oriented software tools:**
  - **SMAC**[1]: While the progress in practical applications has been based on model-free optimization methods, recent progress in model-based approaches promises to lead to the next generation of algorithm configuration procedures. SMAC iterates between fitting models and using them to make choices about which configurations to investigate. It offers the appealing prospects of interpolating performance between observed parameter settings and extrapolating to previously unseen regions of parameter space. It can also be used to quantify the importance of each parameter and parameter interactions. SMAC is a tool for algorithm configuration to optimize the parameters of arbitrary algorithms. The main core consists of Bayesian Optimization in combination with an aggressive racing mechanism to efficiently decide which of the two configurations performs better. SMAC is written in Python3 and continuously tested with Python 3.7, 3.8 and 3.9.
  - **TensorFlow**[2]: It is a free and open-source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on the training and inference of deep neural networks. It combines four key abilities: Efficiently executing low-level tensor operations on CPU, GPU, or TPU; Computing the gradient of arbitrary differentiable expressions; and Scaling computation to many devices, such as clusters of hundreds of GPUs.
  - **TensorFlow Model Optimization**[3]: it is Toolkit is a suite of tools for optimizing machine learning models for deployment and execution. Among many uses, the toolkit supports techniques used to:
    - Reduce latency and inference costs for cloud and edge devices (e.g. mobile, IoT).
    - Deploy models to edge devices with restrictions on processing, memory, power-consumption, network usage, and model storage space.
    - Enable execution on and optimize for existing hardware or new special purpose accelerators.
  - **Keras**[4]: It is a deep learning API written in Python, running on top of the machine learning platform TensorFlow. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result as fast as possible is key to doing good research. Within its main characteristics we can highlight: 1) Simple: it reduces developer cognitive load to free you to focus on the parts of the problem that really

[1] https://github.com/automl/SMAC3
[2] https://www.tensorflow.org/
[3] https://www.tensorflow.org/model_optimization
[4] https://keras.io/about/

matter; 2) Flexible: it adopts the principle of progressive disclosure of complexity, which means, simple workflows should be quick and easy, while arbitrarily advanced workflows should be possible via a clear path that builds upon what you've already learned; 3) Powerful: it provides industry-strength performance and scalability: it is used by organizations and companies including NASA, YouTube, or Waymo.

- **Scikit-learn**[5]: it is a free software machine learning library for the Python programming language. It features various classification, regression and clustering algorithms including support-vector machines, random forests, gradient boosting, k-means and DBSCAN, among others. It is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy.

- **Optimization oriented software tools:**
  - **DEAP**[6]: DEAP is a novel evolutionary computation framework for quick concept prototyping and testing. It aims to make algorithms and data structures more visible. It integrates seamlessly with parallelization mechanisms like multiprocessing.
  - **PyMoo**[7]: PyMoo is an open-source python toolbox for state-of-art multi-objective optimization incorporating evolutionary algorithms. It also supports constrained optimization and parallel execution for computational speedup.
  - **Nevergrad**[8]: Nevergrad, Facebook AI's open-source Python3 library for derivative-free and evolutionary optimization, has several notable new capabilities. It can now work with several objectives (multi-objective optimization) or constraints thanks to these advances. Anyone can use Nevergrad to test and compare multiple methods to a problem or to utilize well-known benchmarks to evaluate how a method compares to the current state of the art because it provides cutting-edge algorithms through an easy-to-use, open Python source.

[5] https://scikit-learn.org/stable/
[6] https://deap.readthedocs.io/en/master/
[7] https://pymoo.org/
[8] https://facebookresearch.github.io/nevergrad/

8 Conclusions

This deliverable has reviewed and analyzed current approaches in the optimization of transport network management within a multi-actor setting. To accomplish such a goal, a set of steps were undertaken. First, we generally describe the main objective and components of the optimization problems in which we have focused our literature review: Signal Vehicle Coupled Control with CAVs, Synchronization of shared and on-demand mobility with transit modes, and Dynamic Congestion Pricing. The reason to approach these categories of problems is because they play a relevant role in the management of traffic at a network level, where different actors and means of transport must be coordinated.

We also reviewed and analysed the optimization models and techniques commonly used in the scientific literature reviewed for the three categories of problems mentioned above. Here it is important to mention that the literature review focused only on papers that address those problems from a pure optimization perspective. In this analysis of the literature, we considered aspects such as the application scope, the optimization models (decision variable, constraints, objective function and modelling approach) and methods used, the experimental benchmark used and the comparison studies performed. Furthermore, we provided information about the main research gaps identified for each problem.

Based on the literature review previously mentioned, we also provided a description and a justification of the particular optimization problems in transport network management in which we will focus on the upcoming tasks of TANGENT. Concretely, the chosen optimization problems were:

- Coupled traffic signal and route planning optimization for CAVs
- Optimization of integration DRT systems with public transit modes
- Synchronization of public transport and Traffic control
- Optimization of Dynamic Congestion Pricing schemes.

In this document, we also reviewed literature related to negotiation and arbitration models for transport network management. This literature review allowed us to identify the role and contributions of these types of models in the coordination of different transportation means at a network level. Finally, we also overview software tools that can be used for the optimization of transport network management.

Annex

SCOPE						
Article Name	**Publication Year**	**Problem Domain**	**Context**	**Spatial Coverage**	**Shared/ on-demand mode**	**CAVs Scenario**
Qian et al., 2021	2021	SVCC	Urban	Network	-	High Penetration of CAVs
Yu et al., 2019	2019	SVCC	Urban	Corridor	-	High Penetration of CAVs
Du et al., 2021	2021	SVCC	Urban	Intersection	-	Mixed Traffic
Yu et al., 2018	2018	SVCC	Urban	Intersection	-	High Penetration of CAVs
Ma et al., 2017	2017	SVCC	Peri-Urban	Intersection	-	High Penetration of CAVs
Zhou et al., 2017	2018	SVCC	Peri-Urban	Intersection	-	High Penetration of CAVs
Li et al., 2014	2014	SVCC	Urban	Intersection	-	High Penetration of CAVs
Niroumand et al., 2020	2020	SVCC	Urban	Intersection	-	Mixed Traffic
Tajalli et al., 2021	2021	SVCC	Urban	Network	-	High Penetration of CAVs
Sun et al., 2020	2020	SVCC	Urban	Intersection	-	High Penetration of CAVs
Li et al., 2018	2018	SVCC	Peri-Urban	Intersection	-	High Penetration of CAVs
Liu and Ceder, 2018	2017	SyncOnDemand	Urban	-	-	Only conventional Traffic
Gkiotsalitis et al., 2022	2022	SyncOnDemand	Urban	-	-	Only conventional Traffic
Lu et al., 2020	2020	SyncOnDemand	Urban	-	Ridesharing	Only conventional Traffic
Kumar and Khani, 2021	2021	SyncOnDemand	Urban	-	Ridesharing	Only conventional Traffic
Stiglic et al., 2018	2018	SyncOnDemand	Urban	-	Ridesharing	Only conventional Traffic
Costa et al., 2021	2021	SyncOnDemand	Urban	-	Ridesharing	Only conventional Traffic
Luo et al., 2021	2021	SyncOnDemand	Urban	-	On-demand	Only conventional Traffic
Auad-Perez and Van Hentenryck, 2022	2022	SyncOnDemand	Urban	-	On-demand	Only conventional Traffic
Liu and Ouyang, 2021	2021	SyncOnDemand	Urban	-	On-demand	Only conventional Traffic
Wu et al., 2020	2020	SyncOnDemand	Urban	-	Bikesharing	Only conventional Traffic
Sun et al., 2019	2019	SyncOnDemand	Urban	-	Demand Responsive Transit	Only conventional Traffic
Levin et al., 2019	2019	SyncOnDemand	Urban	-	On-demand	High Penetration of CAVs
Lau and Susilawati, 2021	2021	SyncOnDemand	Urban	-	On-demand	High Penetration of CAVs
Jia et al., 2020	2020	SyncOnDemand	Urban	-	Ridesharing	Only conventional Traffic
Cheng et al., 2019	2019	DCP	Urban	Network	-	Only conventional Traffic
Chung et al., 2012	2012	DCP	Urban	Intersection	-	Only conventional Traffic
Genser and Kouvelas, 2022	2022	DCP	Urban	Network	-	Only conventional Traffic
Luo, 2019	2019	DCP	Metropoliton	Network	-	Only conventional Traffic
Salazar et al., 2018	2018	DCP	Urban	Network	-	Mixed traffic
Liu et al., 2017	2017	DCP	Urban	Network	-	Only conventional Traffic
Lv et al., 2022	2022	DCP	Urban	Network	-	Only conventional Traffic
He et al., 2017	2017	DCP	Urban	Corridor	-	Only conventional Traffic
Zhang et al., 2019	2019	DCP	Urban	Corridor	-	Only conventional Traffic
Cheng et al., 2021	2021	DCP	Urban	Network	-	Only conventional Traffic

Table 6: Summary table for scope

				Optimization Model				Optimization Method
Article Name	Problem Domain	Architecture	Control Level	Decision Variables	Constraints	Objective Function	Modelling Approach	
Qian et al., 2021	SVCC	Centralised	Multiple vehicles	Signal timings, Vehicle trajectory, Travel Route, Departure time	Route feasibility, Communication Constraint, Energy Consumption	Traffic Flow Efficiency	Mathematical Programming	CPLEX Solver
Yu et al., 2019	SVCC	Centralised	Multiple vehicles	Vehicle trajectory, Travel Route	Communication Constraint, Energy Consumption	Traffic Flow Efficiency	Mathematical Programming	Gurobi
Du et al., 2021	SVCC	Decentralised	Individual Vehicle	Vehicle Dynamics, Signal timings, Vehicle trajectory	Energy consumption constraint, Communication constraint	Traffic Flow Efficiency, Economic and environmental impact objective	Simulation based	SUMO
Yu et al., 2018	SVCC	Decentralised	Multiple vehicles	Vehicle Dynamics, Signal timings, Vehicle trajectory	Energy consumption constraint, Communication constraint	Traffic Flow Efficiency, environmental impact objective	Mathematical Programming	Gurobi
Ma et al., 2017	SVCC	Centralised	Multiple vehicles	Vehicle Dynamics, Vehicle trajectory	Energy consumption constraint,	Traffic Flow Efficiency, Economic and environmental impact objective	Simulation based	parsimonious shooting heuristics
Zhou et al., 2017	SVCC	Centralised	Multiple vehicles	Vehicle Dynamics, Vehicle trajectory	Energy consumption constraint,	Traffic Flow Efficiency, Economic and environmental impact objective	Simulation based	parsimonious shooting heuristics
Li et al., 2014	SVCC	Centralised	Multiple vehicles	Vehicle Dynamics	Energy consumption constraint,	Economic and environmental impact objective	Mathematical Programming	Bisecting search
Nirouman d et al., 2020	SVCC	Centralised	Multiple vehicles	Signal timings, Vehicle dynamics	Energy consumption constraint,	Traffic flow efficiency	Mathematical Programmin	CPLEX solver
Tajalli et al., 2021	SVCC	Centralised	Multiple vehicles	Signal timings, Vehicle dynamics	Energy consumption constraint,	Traffic flow efficiency	Simulation based	-
Sun et al., 2020	SVCC	Decentralised	Individual Vehicle	Vehicle trajectory, Signal timings	Communication Constraint, Energy Consumption	Traffic Flow Efficiency, Economic impact objective	Mathematical Programming	Dynamic Programming
Li et al., 2018	SVCC	Centralised	Multiple vehicles	Vehicle dynamics, Signal timings	Communication Constraint, Energy Consumption	Traffic flow efficiency	Simulation based	MATLAB
Liu and Ceder, 2018	SyncOn Demand	-	-	Vehicle Departure schedule	Travel time, passenger waiting time	Trip demand coverage	Mathematical Programming	Mathematical program solver
Gkiotsaliti s et al., 2022	SyncOn Demand	-	-	Vehicle Departure schedule	-	System wide cost	-	-
Lu et al., 2020	SyncOn Demand	-	-	Total travel time limit, vehicle capacity	Trip demand coverage	System wide cost	Mathematical Programming	Python-GAMS
Kumar and Khani, 2021	SyncOn Demand	-	-	Driver-rider matching	Passenger waiting time,total travel time	optimal driver passanger matching, passenger travel time.,system wide cost.	Mathematical Programming	Python
Stiglic et al., 2018	SyncOn Demand	-	-	Driver-rider matching	Passenger waiting time,total travel time	optimal driver passanger matching, passenger travel time.,system wide cost.	Mathematical Programming	CPLEX solver
Costa et al., 2021	SyncOn Demand	-	-	vehicle departure schedule	passanger waiting time, vehicle capacity, trip demand coverage	passanger travel time, optimal driver passanger matching	Simulation	-

					Optimization Model			Optimization Method
Luo et al., 2021	SyncOn Demand	-	-	Shared vehicle capacity, total travel time limit	passanger waiting time, vehicle capacity, trip demand coverage	System wide cost, Passanger travel time	Mathematical Programming	Mathematical program solver
Auad-Perez and Van Hentenryck, 2022	SyncOn Demand	-	-	Vehicle departure schedule, shared vehicle capacity	Passenger waiting time , Vehicle capacity	System wide cost	Mathematical Programming	Mathematical program solver
Liu and Ouyang, 2021	SyncOn Demand	-	-	Vehicle departure schedule	Passenger waiting time , Vehicle capacity	System wide cost	Mathematical Programming	Mathematical program solver
Wu et al., 2020	SyncOn Demand	-	-	vehicle departure schedule, shared vehicle capacity	Trip demand coverage, vehicle capacity	System wide cost	Mathematical Programming	Mathematical program solver
Sun et al., 2019	SyncOn Demand	-	-	vehicle departure schedule, shared vehicle capacity	Passanger waiting time, total travel time limit	passanger travel time	Mathematical Programming	CPLEX solver
Levin et al., 2019	SyncOn Demand	-	-	vehicle departure schedule, shared vehicle capacity	Passanger waiting time, total travel time limit	passanger travel time	Mathematical Programming	CPLEX solver
Lau and Susilawati , 2021	SyncOn Demand	-	-	vehicle departure schedule	Passanger waiting time, total travel time limit	total demand coverage, system wide cost	Simulation	VISUM
Jia et al., 2020	SyncOn Demand	-	-	vehicle departure schedule, shared vehicle capaity	Trip demand coverage	passanger travel time	Heuristic	NSGA-2, PSO
Cheng et al., 2019	DCP	-	-	Distance toll, congestion charge rate	Traffic flow constraints	Total system travel time	Heuristic	Aritificial bee colony optimization
Chung et al., 2012	DCP	-	-	Congestion charge rate	Dynamic user equilibrium constraints	Total system travel time	Heuristic	Simulated annealing
Genser and Kouvelas, 2022	DCP	-	-	Regional time varying pricing	-	Total revenue maximization	Mathematical Programming	Machine learning tool (Others)
Luo, 2019	DCP	-	-	Congestion charge rate	dynamic user equilibrium	Total revenue maximization	Mathematical Programming	Bayesian optimization
Salazar et al., 2018	DCP	-	-	Congestion charging rate	Traffic flow constraints	Total travel time and systemwide cost	Mathematical Programming	Mathematical program solver
Liu et al., 2017	DCP	-	-	Distance toll	Traffic flow constraints	System wide cost	Mathematical Programming	Mathematical program solver
Lv et al., 2022	DCP	-	-	Congestion charging rate	Traffic flow constraints	System wide cost and travel time	Mathematical Programming	Mathematical program solver
He et al., 2017	DCP	-	-	Congestion charging rate	Traffic flow constraints	Total revenue and total travel time	Simulation	Krigging
Zhang et al., 2019	DCP	-	-	Congestion charging rate	Traffic flow constraints	Total revenue and total travel time	Simulation	-
Cheng et al., 2021	DCP	-	-	Distance toll	Traffic flow constraints	Total travel cost	Heuristic	Whale optimization algorithm

Table 7: Summary table for optimization model and method

			Experimental Design			Comparative study	
Article name	**Problem Domain**	**Datatype**	**Location**	**Problem Dimension**	**Compared Methods**	**Compared Metrics**	**Type of Comparison**
Qian et al., 2021	SVCC	Synthetic	Virtual simulation	46 nodes and 122 links	-	-	no comparison
Yu et al., 2019	SVCC	Synthetic	Virtual simulation	1 corridor with 4 links	Co-ordinated fixed time control	Average delay, total throughput	Baseline algorithm comparison
Du et al., 2021	SVCC	Synthetic	Virtual simulation	-	CACC, GlidePath	Fuel consumption, total CO2 emissions, average delay	Baseline algorithm comparison
Yu et al., 2018	SVCC	Synthetic	Virtual simulation	3 & 7 signalized intersection	Modified IDM	Fuel consumption, average delay	Baseline algorithm comparison
Ma et al., 2017	SVCC	Synthetic	Virtual simulation	4 arm intersection	-	Fuel consumption, average delay	Self-comparison
Zhou et al., 2017	SVCC	Synthetic	Virtual simulation	Freeway	IDM	Fuel consumption, average delay	Baseline algorithm comparison
Li et al., 2014	SVCC	Synthetic	Virtual simulation	Freeway	Newell Method	Fuel consumption, average delay	Baseline algorithm comparison
Niroum and et al., 2020	SVCC	Synthetic	Virtual simulation	Freeway	Parsimonious Shooting heuristic	Fuel consumption, total CO2 emmission	Baseline algorithm comparison
Tajalli et al., 2021	SVCC	Synthetic	Virtual simulation	Intersection	CORSIM	Average delay, total throughput	Baseline algorithm comparison
Sun et al., 2020	SVCC	Synthetic	Virtual simulation	Intersection	Traditional actuated signal control	Total delay	Baseline algorithm comparison
Li et al., 2018	SVCC	Synthetic	Virtual simulation	Network of 20 Intersection	Traditional actuated signal control	Total delay, total throughput	Baseline algorithm comparison
Liu and Ceder, 2018	SyncOnDemand	Synthetic	Virtual simulation	-	-	-	-
Gkiotsalitis et al., 2022	SyncOnDemand	Real	Virtual simulation	-	-	-	-
Lu et al., 2020	SyncOnDemand	Real	Virtual simulation	-	-	-	-
Kumar and Khani, 2021	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Stiglic et al., 2018	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Costa et al., 2021	SyncOnDemand	Real	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Luo et al., 2021	SyncOnDemand	Real	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Auad-Perez and Van Hentenr	SyncOnDemand	Synthetic	Virtual simulation	-	-		

			Experimental Design			Comparative study	
yck, 2022							
Liu and Ouyang , 2021	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost, private vehicle km,	Self-comparison
Wu et al., 2020	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost, private vehicle km,	Self-comparison
Sun et al., 2019	SyncOnDemand	Synthetic	Virtual simulation	-	CPLEX	Total travel time, minimum waiting time, total travel cost	Baseline algorithm comparison
Levin et al., 2019	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Lau and Susilawati, 2021	SyncOnDemand	Synthetic	Virtual simulation	-	-	Total travel time, minimum waiting time, total travel cost	Self-comparison
Jia et al., 2020	SyncOnDemand	Synthetic	Virtual simulation	-	NSGA-2, MOPSO	Total travel time, minimum waiting time, total travel cost	Baseline algorithm comparison
Cheng et al., 2019	DCP	Synthetic	Virtual simulation	-	JDTT	Total travel time	Baseline algorithm comparison
Chung et al., 2012	DCP	Synthetic	Virtual simulation	-	Simulated annealing	Total travel cost	Baseline algorithm comparison
Genser and Kouvelas, 2022	DCP	Synthetic	Virtual simulation	-	-	-	-
Luo, 2019	DCP	Synthetic	Virtual simulation	-	Regression model	Total travel cost	Baseline algorithm comparison
Salazar et al., 2018	DCP	Synthetic	Virtual simulation	-	AMoD	Total travel time & cost	Baseline algorithm comparison
Liu et al., 2017	DCP	Synthetic	Virtual simulation	-	-	-	-
Lv et al., 2022	DCP	Synthetic	Virtual simulation	-	BLP	Total emission and travel time	Baseline algorithm comparison
He et al., 2017	DCP	Real	Virtual simulation	-	BLP	Total emission and travel time	Baseline algorithm comparison
Zhang et al., 2019	DCP	Real	Virtual simulation	-		Total toll revenue	Self-comparison
Cheng et al., 2021	DCP	Synthetic	Virtual simulation	-	-	Total toll revenue	Self-comparison

Table 8: Summary table for experimental design and comparative study

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