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# Impact of stakeholder cooperation for centralized route guidance and full automated vehicle compliance

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## Abstract

Route guidance in traffic management aims to improve traffic network performance aligned with a system optimum. However, service providers commonly offer user optimal travel advice that can negatively impact centralized route guidance. This paper quantifies and demonstrates the impact of different policy strategies for a centralized route guidance systems where road authorities and service providers work together in a coordinated approach. Cooperation through an intermediary is considered with various policy strategies that consider different approaches and levels of cooperation between road authorities and service providers, which are evaluated using traffic modelling. A use case for the ring network of Milan shows that cooperation between the two parties has the potential to get the best out of the measure by utilizing a system optimum approach, while still allowing service providers to offer individual travel advice. The results of the modelled case study clearly show that the two approaches of far-reaching cooperation and increased compliance have a greater positive effect on traffic network performance in terms of reduced delays, reduced congestion and total time spent. In addition, the future presence of Connected Automated Vehicles (CAV) is also considered in which these vehicle demonstrate full compliance. This shows that with increasing percentage of CAVs that route guidance can have a substantial positive effect compared to low compliance or a smaller penetration rate of automated vehicles.

# 1 Introduction

Traditionally, traffic management has been effectively applied through road-side interventions by (National) Road Authorities (RA) by influencing traffic flow, traffic demand and traffic characteristics to improve traffic throughput, safety and emissions. Increasingly, other sources of traffic information and guidance are being offered and used that are not centrally coordinated by RAs. A primary example is in-car navigation devices. Approximately 90% of the people in Europe own navigation equipment, while a survey in The Netherlands indicated that 80% of the people who travel for business or who go for a day out use a navigation application (1). And of these people, 35% receive online congestion updates and are able to change their routes based on real-time traffic conditions. Service Provider (SP) delivered information is offered as individual advice and operates on the principle of an on-trip User Equilibrium (UE), in which the travel time for that individual user is minimized based on current traffic circumstances (2). This contradicts RA road-side traffic management information that is generally designed for (partial) System Optimum (SO), which entails that the total sum of all vehicle delays are minimized to enhance the total system performance (3; 4), often measured by traffic throughput. Hence, UE-focused advice offered by SPs acts as a system disturbing process and has been shown to lead to a deterioration in traffic performance (5).

In past years, there have been efforts to counter the increasing negative effects of SP travel and route guidance advice through cooperation between RAs and SPs to achieve common objectives and prevent deterioration of traffic performance. However, Koller-Matschke (6) found that there are some serious concerns about the commitment by SPs and RAs to collaborate. To illustrate this, a large field study with 20.000 participants in the region of Amsterdam (7) did not lead to a significant improvement of the traffic flow performance (8). The conclusion of the evaluation found that the committed penetration of participants was too small to influence the system performance and that the greatest benefits of system optimum routing were mainly obtained by non-participating vehicles. Houshmand, Wollenstein-Betech and Cassandras (9) state that such an outcome may lead to participating SPs becoming less competitive compared with non-participating SPs as it is unclear whether road users would accept this kind of route guidance and what the benefits would be for the network performance.

Previous studies have shown the full potential of full participation and compliance in a centralized SO route guidance system (El Hamdani & Benamar, 2018; Kuru & Khan, 2020). However, in practice, many road users are not influenced by traffic information (Gan & Chen, 2013; Iraganaboina et al., 2021; Reinolsmann et al., 2020) and not everyone is willing to accept it voluntarily (Bonsall & Joint, 1991; Mariotte et al., 2021). Furthermore, the real-time traffic information provided by SPs is in most cases the instantaneous travel time and not the time the road user will experience. Taking into account a better prediction of future traffic states would improve traffic information for the road users, but would also be better for the system (Backfrieder et al., 2016). Also, multiple regulation strategies with voluntary and mandatory elements have been suggested to improve the impact of the centralized route guidance systems (Bagloee et al., 2016). Regulations may solve the lack of compliance, but are often not the preferred alternative of policymakers and may even not be necessary.

A recent example of RA-SP cooperation was proposed and executed in the cooperation framework which was part of the SOCRATES$^{2.0}$ project (SOCRATES$^{2.0}$, 2020). The SOCRATES$^{2.0}$ project brought road authorities, service providers and car manufacturers together and applied a coordinated approach for smart route advice and also tested this in multiple practical trials in Europe. In this approach, four intermediary roles (strategy table, network manager, assessor, and network monitor) coordinate the information flow between RA and SP and the given route advice to ensure that a good balance can be found between SO and UE travel and route advice. However, the results of the project remained inconclusive to the potential effects of this cooperation, mainly due to limitations in the execution in practice. The potential effects of cooperation in the case of an incident were shown in a simulation study by Taale (2020). Harmonizing route guidance in the event of a tunnel closure was shown to lead to 17% less delay in the Stockholm network. A final consideration is also made for future opportunities that Connected Automated Vehicles (CAV) may bring about. Their emergence and connection to real-time route guidance is hypothesized to make it easier to divert traffic en-route as many CAVs may demonstrate full compliance, especially in the case of drivers/occupants that are out of the driving loop (Chen et al., 2022). Studies have shown that a strong effect of CAVs can be reached, even with moderately low penetration rates (Houshmand, Wollenstein-Betech, & Cassandras, 2019), which may lead to even a moderately strict regulation strategy being very effective and satisfy road users, policymakers and service providers.

In this paper, we aim to operationalize the cooperation concept of the SOCRATES$^{2.0}$ to model and demonstrate if, and how much, RA-SP cooperation can lead to improvements in traffic performance, beyond the current and future scenarios that SPs apply a counteractive UE approach to RAs SO approach. The main contribution of the paper lies with testing and demonstrating the various strategies. The approach considers different regulation strategies for a centralized route guidance system in which SPs and RAs are assumed to work together to achieve common goals. The presence of CAVs with full compliance is also considered. In Section 2, we present the applied methodology, which includes the actor's interaction and regulation, as well as policy strategies. Thereafter, we present the applied modelling approach in Section 3, with the case study setup in Section 4 and results of a case study applying the methodology to the ring network of Milan in Section 5. Finally in Section 6, we reflect on the strategies and draw our conclusions thereafter. A fourth blank row should be included.

# 2 Methodology

## *2.1 Overview of methodology*

The approach taken in this paper loosely follows that applied within the SOCRATES framework, which in turn is based on the state-of-the-art from science and practice, and is extended to use traffic modelling for impact assessment. An overview of the total methodology to determine the impacts of different policy strategies from the cooperation strategy is given in *Figure 1*. The **cooperation strategy** is constructed based on an **interaction scheme**, detailing the process from data acquisition to measure selection and influence on end users, together with the network layer approach that describes the **actor resources and objectives**, primarily from RA and SPs. **Policy strategies** are derived based on the cooperation strategy, which are translated into scenarios that are evaluated using a **traffic model** to finally determine the impact of each scenario quantified in terms of traffic throughput and performance. Each part of the methodology is described in detail in the remainder of this section, while the modelling approach is presented in the section thereafter.

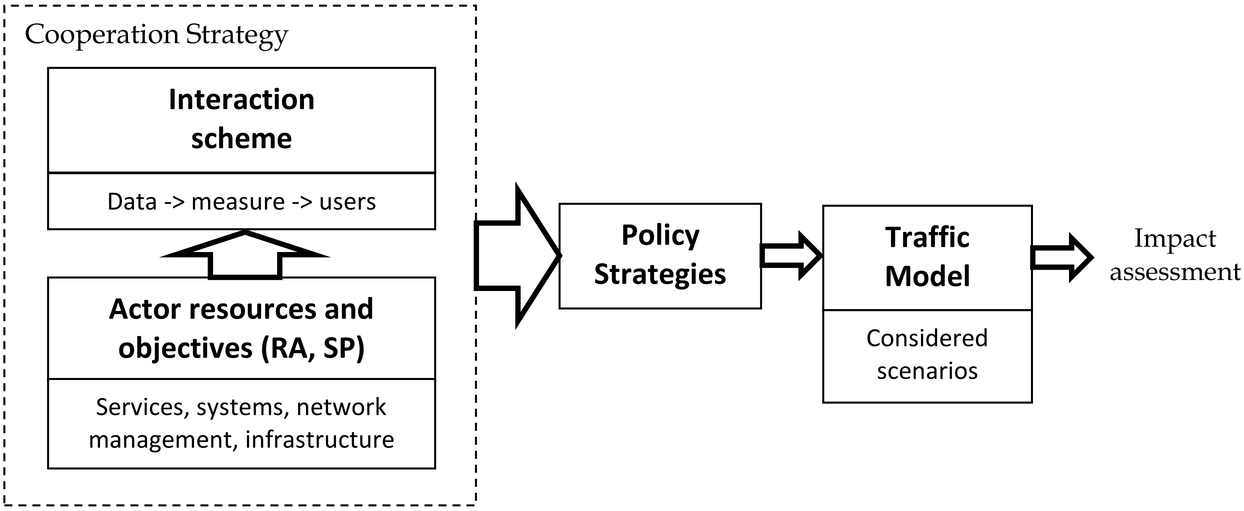


*Figure 1. Research methodology for impact assessment of RA-SP coordinated route guidance*

## 2.2 Cooperation strategy

*Actors and cooperation*

Coordination strategies are essential for effective traffic management, especially when multiple actors are involved in providing traffic information and services to road users. The SOCRATES$^{2.0}$ project developed a novel cooperation framework that defines three levels of coordination among road authorities, service providers, and car manufacturers: strategic, tactical, and operational (Yperman, 2019; Groenendijk et al., 2021). At the strategic level, coordination involves setting common objectives, principles, and business models for traffic management (Yperman, 2019). This requires a mutual understanding of each actor's interests, roles, and responsibilities, as well as a clear definition of the value proposition and revenue streams for each service (Yperman, 2019). At the tactical level, coordination involves sharing relevant data and aligning actions through a network manager role (Koller-Matschke, 2018; Yperman, 2019). The network manager is responsible for monitoring network performance, identifying traffic problems and opportunities, proposing solutions, and facilitating agreements among actors. The network manager also acts as a data broker that collects, processes, and distributes data from different sources to support traffic management decisions (Koller-Matschke, 2018). Finally, at the operational level, coordination involves implementing interactive traffic management measures and services that can influence road users' behaviour and route choices (Koller-Matschke, 2018; Yperman, 2019). These measures and services are based on four use cases: network monitoring, urban–interurban routing, smart tunnel service, and eco-routing. They aim to provide road users with accurate, timely, and personalized information that can improve their travel experience while reducing congestion and emissions (Yperman, 2019).

The cooperation framework in the SOCRATES$^{2.0}$ project describes the coordinated approach for smart route guidance. Four intermediary roles are established with an overall objective to enable coordinated end-user services possible:

- Network Monitor
- Strategy Table
- Network Manager
- Assessor

Each 'role' describes a critical process and the related actors required to construct the entire chain of events that allow coordination between RAs and SPs to take place using all available resources.

The network monitor creates a uniform data foundation and combines the data collected by the service providers to create a commonly agreed view of the network. The strategy table focusses on the measures and interventions that should be taken, under the prevailing traffic and network conditions and which corresponding objective is pursued. The network manager is a technical platform that executes the measures and interventions as dictated from the strategy table, while the assessor acts as a feedback loop to verify the performance of the network manager to meet the objectives laid out by the strategy table. Four objectives are targeted on the strategy table, namely:

1. Safer, cleaner and more efficient traffic flow and better use of the road capacity
2. Better services to the road users and better quality of life for citizens,
3. Cost-effective traffic management by optimizing the use of existing road capacity
4. Economic growth and the creation of more jobs by reducing traffic problems and by creating new business opportunities.

The demands and objectives of both commercial stakeholders, such as revenue and customer satisfaction, and authorities, such as fast, safe, and environmentally friendly traffic, are evident. These interests overlap to some extent but differ on other aspects, and thus, finding a cooperation model that appeals to all parties may pose a challenge (Huisken et al., 2020). Also, sometimes these objectives can be contradictory. A better service to road users could lead to increased traffic flows in urban areas with negative impact on the living environment in terms of safety, emissions and noise. This will not improve the quality of life for citizens and so a balance has to be sought.

While the objectives in themselves can be viewed as abstract, a common denominator of these objectives is the reduction of congestion (Koller-Matschke, 2018). However, this objective should not be sought at any cost. For example, excessive detours could help reduce congestion, but would lead to other detrimental effects. In terms of traffic performance, these detrimental effects would primarily relate to increased travel time and distance. The reduction of the total travel time is therefore also considered as a main objective of the cooperation for smart routing. As congestion leads to a longer travel time, the reduction of congestion is also included in the objective to minimize the total travel time.

It should be noted that the implementation of these roles is not part of this study. It is assumed that all roles are implemented properly and when mentioning the intermediary, we refer to the combination of these separated roles as part of the cooperation strategy (Koller-Matschke, 2018). The concept of separating the network management tasks by implementing an intermediary is a well-known principle in network industries, where a distinction is often made between the network management tasks and the actors that are responsible for these tasks (Jaag & Trinkner, 2011). As such, the intermediary cooperation strategy considered from SOCRATES$^{2.0}$ is translated, based on Jaag and Trinkner (2011), to yield the tasks and responsibilities as shown in Figure 2. This especially highlight the different roles that RAs and SPs have in the cooperation framework.

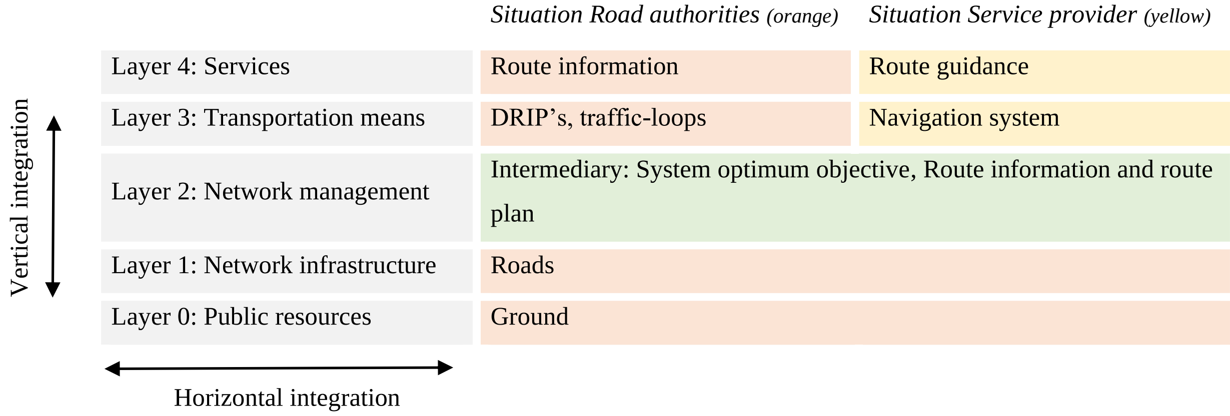


*Figure 2. Segregation of Network layers vertical integrations per actor, suggested situation road network with in green the new intermediary, based on (Jaag & Trinkner, 2011)*

*Actor interaction*

To further clarify interactions and cooperation between RAs and SPs upon implementation of an intermediary, the explicit flow of data and information is captured in the interaction scheme, shown in Figure 3. All actors may have data sensors and can obtain their own data from a variety of sources. In an ideal system, actors aggregate their data and share their data with the intermediary which aggregates all available data to one data set and which presents the common truth about the network state. The intermediary calculates the optimum routing and instructs all actors on which measures should be taken, which for route guidance will often be routing advice. The actors actuate the measures and the road users obtain the routing information.

Huisken et al. (2020) highlight that although there is research on cooperation within the traffic management domain (Hegyi et al., 2001; Hoogendoorn et al., 2003; Kammoun et al., 2014), it predominantly addresses joint control strategies, for example through scenario deployment. Models suitable for cooperation between multiple public and private organizations—with the aim of establishing a common strategic, tactical, and operational framework—are scarce or not well described (Koller-Matschke, 2018; Huisken et al., 2020; Metz, 2022). A major contribution of the SOCRATES$^{2.0}$ project was therefore the definition of common ground for cooperation on a strategic level for public–private traffic management, building on the concept of Traffic Management 2.0 (TM2.0) as described by Rehrl et al. (2016) and Vlemmings et al. (2017). We describe the required details and justification of this approach here for the demonstration of these strategies in traffic, while for further reading on SOCRATES$^{2.0}$, we point to the various technical reports and papers (Koller-Matschke, 2018; Yperman, 2019; Groenendijk et al., 2021).

In the option shown in Figure 3, one intermediary is established for road authorities while SPs share their data. In this case, all data of participating actors can be shared. The traffic management centres adapt their measure based on what SPs do. It should be noted that certain SPs may decide to operate partially within the cooperation or even entirely independently to it. In the figure, SP2 are the SPs that only share and obtain data to improve their service to offer the fastest routes for their users. This group does not execute the measures dictated by the intermediary and will not offer SO routing. SP3 represents SPs that act entirely independently. This group does not connect with the intermediary and is also not involved with data sharing, basically acting entirely independent to the cooperation, also in regard to the routing advice given, which is purely UE. It is assumed that the Traffic Management Centres (TMC) are completely compliant with the intermediary. This aligns and is supported by literature on other Traffic Management Systems (TMS) that are composed of various application and that aim to improve overall traffic efficiency and safety (De Souza et al., 2017). From this is should be clear that engagement of SPs is important and that different levels of engagement can influence the extent to which the cooperation can be effective.

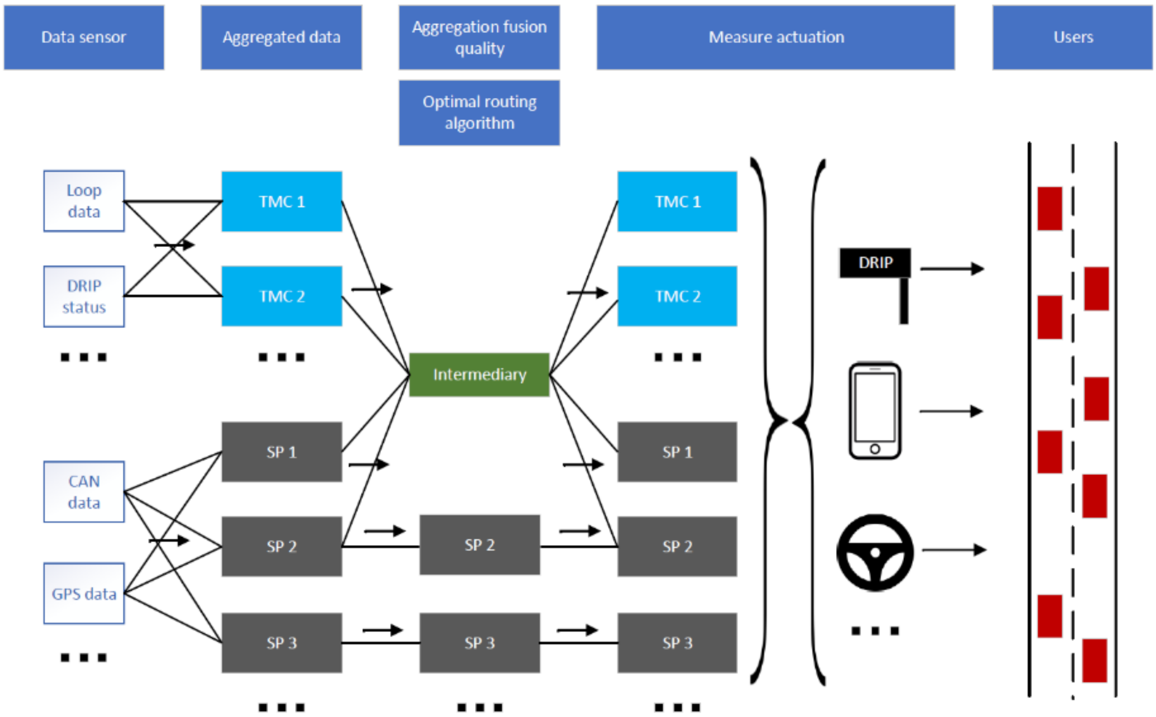


*Figure 3. Interaction scheme with voluntary use of an intermediary with bypass behavior, based on intermediary option three from proposed cooperation framework SOCRATES$^{2.0}$ (Koller-Matschke, 2018)*

### 2.3 *Policy strategies*

From the scheme shown and discussed in the previous paragraph, it is clear that action by SPs will influence the effectiveness of the cooperation strategy and in turn the ability to guide traffic in a SO way. In this paper, we are interested to study what the effectiveness is of different regulation and policy strategies to obtain the best network performance under various conditions. Government has the ability to construct and enforce certain regulations obliging SPs to adhere to cooperation strategies and even complying road users to adhere to route advice (Huisken et al., 2019). Below, we consider three levels of regulations that are analysed later in Section 3 of this paper. The considered regulatory measures and policy strategies are as follows:

- **$\Omega_0$: Base reference strategy: Status quo**

In this strategy, no regulations are implemented and eventually, all vehicles will drive a perceived user equilibrium without perfect knowledge of the network.

- **$\Omega_1$: Implementation of the intermediary with voluntary participation**

In this strategy, an independent intermediary is established which makes cooperation possible and makes it possible for SPs to exchange data to improve their user equilibrium algorithm. The intermediary aggregates the data of all participating actors and determines the optimal set of measures based on a commonly agreed strategy table.

- **$\Omega_2$: Compulsory SP participation with the intermediary services**

In this strategy, the intermediary is active as in $\Omega_1$, while all actors are obliged to use the services of the intermediary. When this regulation is in force, SPs cannot directly offer UE route advice to their users. SPs are obligated to execute the instructions of the intermediary and offer the congestion avoiding SO routing to their users.

- **$\Omega_3$: Compulsory road user compliance of given route guidance**

The final strategy builds on $\Omega_1$ and $\Omega_2$ by also making road user compliance of the given route advice mandatory. Road users are forced to comply with the route advice to achieve SO. In this case, all guided vehicles will avoid congestion to improve network traffic performance.

The following section goes into the modelling process that is applied to investigate the effectiveness of these policy strategies.

# 3 Model setup

To address different policy strategies and scenarios, we make use of a macroscopic traffic model with route assignment and capable of demonstrating the influence of different forms of travel information and compliance. The applied model is the Simulation-Based Dynamic Traffic Assignment Model (SBDTA): MARPLE, which is detailed in this sub-section. As well as detailing this model, we also give justification for the choice of this model and its context in the landscape of DTA modelling approaches.

### 3.1 *Traffic Modelling and MARPLE*

If we consider the time aspect, there are three main types of traffic assignment models: Static Traffic Assignment (STA) models, semi-dynamic traffic assignment and Dynamic Traffic Assignment (DTA) models (Bliemer et al., 2017). STA models assume that traffic flows are constant over time, and are usually used for long-term planning and analysis. STA models typically solve for a one-time assignment of traffic flows on a transportation network based on assumptions about traveller behaviour and road network characteristics. STA models have their limitations in applications for which traffic evolution over time is critical (Peeta & Ziliaskopoulos, 2001; Wang et al., 2018), but are still valuable in their application as transport planning tools. Semi-dynamic traffic assignment models are essentially a series of connected STA models (see Brederode et al., 2023 for an overview). Semi-dynamic traffic assignment models incorporate multiple time periods for route selection, where the residual traffic of one period can transfer to the subsequent periods. However, unlike DTA models, the semi models typically consider only a single time step for network loading during each route choice period, which entails flow propagation through the network. DTA models consider the temporal and spatial variations in traffic flows, and are used for short-term prediction and control of traffic flows. DTA models take into account the feedback between demand and supply, and the interactions between vehicles, and the transportation network. DTA models can also capture the effects of incidents, congestion, and other unpredictable events on traffic flows (Mahmassani, 2001).

Within the category of dynamic traffic assignment models, there are several subtypes, which include Simulation-Based Dynamic Traffic Assignment (SBDTA) models. SBDTA models use simulation techniques to capture the complex interactions between travellers, vehicles, and the transportation network, and are well-suited for real-time prediction and control of traffic flows (Peeta & Ziliaskopoulos, 2001), but also to consider the impacts of incidents and accidents, and provide realistic travel time estimates (Wang et al., 2018; Saw et al., 2015; Sundaram et al., 2011). These models have been used in both research and practice to evaluate various transportation policies and technologies. For example, Abdelghany et al. (2007) use an SBDTA model to evaluate and plan Bus Rapid Transit (BRT) services in urban transportation networks, and Antoniou et al. (2011) applied a DTA model to evaluate the effectiveness of traffic diversion strategies for non-recurrent congestion and for incident management. Routing options combined with various traffic management options were also investigated by Burghout, Koutsopoulos and Andreasson (2010) for incidents. Emmerink et al. used an SBDTA model to study the impact of traveller information on travel behaviour and congestion, recurrent and non-recurrent (42; 43). Zambrano-Martinez et al. (2019) further proposed an approach based on load balancing through analysis of demand to predict future behaviour and to optimize route choice in an urban setting with future automated traffic in mind. Other authors have dived deeper into detailed route optimization for such cases, with Liebig et al. (2017) offering a good example of how advanced regression techniques with strategically positioned sensor observations. Pricing strategies for congestion charging has also been considered (Loder et al., 2022). These studies show that various ITS approaches have been assessed using these models. However, addressing route guidance problems with SBDTA models requires that the model can deal different levels of information and different definitions of a user equilibrium.

Therefore, in this study, we apply the SBDTA model MARPLE for route guidance and the impact of policy strategies (Taale, 2020). MARPLE stands for Model for Assignment and Regional Policy Evaluation (Taale, 2022). For every time period, the assignment module distributes traffic flows over available routes and uses a dynamic network loading model to simulate these flows in the network (Taale, 2008). The travel times or costs per period from the simulation are used for a redistribution of the traffic flows, using the multi-nominal logit model with overlap in routes, as defined by Cascetta et al. (1996). The assignment module is dynamic in the sense that for every time period the distribution of traffic over the available routes can be different, based on travel times or costs for that period. These travel times or costs are generated by the dynamic network loading module which propagates traffic through the network, taking into account capacities, intersection delays, blocking back, etc. The propagation of traffic on the links is done using travel time functions for different types of links (Taale, 2008). The node model distributes the flow on the incoming links over the outgoing links using turning rates calculated from the assigned route flows. The node model complies with the first 6 of the 7 criteria as described by Tampère et al. (2011). In some cases the invariance principle is not satisfied.

The assignment and simulation step are repeated until the model converges to a dynamic user equilibrium. In this way the model mimics the day-to-day learning experience of drivers. The model allows for two different assignment algorithms: a Dynamic Deterministic User Equilibrium

(DDUE) algorithm and the Dynamic Stochastic User Equilibrium (DSUE) algorithm. For this study the DSUE is the appropriate assignment approach, where the travel information for drivers of the network state is incomplete and drivers choose their perceived fastest route. In the DSUE algorithm, the completeness or quality of the information for the road user can be varied with the parameter θ. This parameter changes the size of the stochastic uncertainty for the DSUE assignment, which indicates the chance that the chosen route is the fastest.

In MARPLE, also different user classes can be defined. A user class represents a group of road users with the same routing behaviour with different values of θ and thus with a different route choice behaviour towards changes in the network situation. There are also habitual road users who do not change their route at all. Habitual routing behaviour consists mostly of previous experiences of the driver. It is assumed that habitual drivers, who cannot be influenced by traffic information, will take the perceived fastest route according to uncongested traffic conditions.

### *3.2 Congestion avoiding user equilibrium algorithm*

In this study, route choice by cooperative automated vehicles makes use of a congestion avoiding user equilibrium algorithm. A congestion avoiding approach can have a positive effect on the traffic performance (Summerfield et al., 2021). Congestion avoiding is implemented with a perceived time penalty for links above a certain flow/capacity threshold. With this time penalty, participating road users avoid routes over (nearly) congested links. This reduces congestion and for that reason the average travel time. In the best-case scenario, it also prevents congestion. The applied time penalties are given in the scenario descriptions in the following section.

The implementation of congestion avoidance strategies to improve traffic performance can be described as follows: When a single link becomes congested, all routes utilizing that particular link will experience an increase in perceived travel time, expressed as a percentage of the current travel time. Vehicles utilizing congestion avoidance tactics will opt for alternate routes if the additional travel time associated with the detour is less than the time penalty incurred by remaining on the congested path. This will result in a decrease in traffic flow on the congested link, ultimately leading to reduced travel times for all vehicles until such time as the congestion dissipates without the need for detours. A previous study showed that avoiding all congestion can lead to excessive detours which could lead to a reduced effect on the total travel time (Summerfield et al., 2021). The chosen time penalty approach will prevent this, because the time penalty value is the longest additional travel time that would be accepted which prevents excessive detours to occur.

### *3.3 Assumptions for the scenarios*

The cooperation model with the specified policy strategies is converted into simulation input as shown in Figure 4, which shows how traffic is assigned to specific groups of routing behaviour. This figure includes a number of assumptions. The scheme divides the traffic into two groups: human drivers and CAV. All CAVs are influenced by service providers and have perfect compliance. Human drivers can be influenced by service providers, by the traffic management centre or are not influenced at all. Research shows that 30% to 35% of the traffic can be influenced by traffic information (KiM, 2017; Gan & Chen, 2013; Iraganaboina et al., 2021; Reinolsmann et al., 2020). Therefore, for human drivers it is assumed that 70% cannot be influenced (parameter A). For the sake of this study, the CAVs are assumed to have the same driving dynamics as the human driven vehicles. A commonly applied measure for routing traffic is the dynamic route information panel (DRIP). Unfortunately, the provided information is only relevant for 30% to 40% of the road users (KiM, 2017), and only 5% to 6% of the road users is willing to change route for small travel time benefits (Wardman, Bonsall, & Shires, 1996). Therefore, it is assumed that only 10% may be willing to change route based on information from the traffic management centre (parameter B in Figure 4) and that 20% of the traffic can be influenced by information from the service providers (parameter C in Figure 4). Since 91% of the road users has navigation equipment available (KiM, 2017), and 25% of all road users are using it on a regular basis (KiM, 2017; Knapper et al., 2016), this assumption appears to be valid. We also assume that there is no overlap in drivers who are influenced by the traffic management centre and those influenced by the information from service providers. Drivers who have both types of information tend to use the personalized information from the service providers.

The distribution of the group which is influenced by the service providers depends on the scenario. Without implementing the intermediary, parameter H is set to 100% because no data is shared. While policy regulation $\Omega_1$ is active, F, G and H can all be non-zero and the values depend on the scenario. With the regulation $\Omega_2$ active, parameters G and H are 0% and F becomes 100%, which is the situation for which all road users influenced by the service providers, use the congestion avoiding routing. The compliance of the road users to reroute depends on the compliance algorithm, described in the following paragraph. Only in the situation where policy regulation $\Omega_3$ is active will the compliance be 100%. In all other situations, vehicles who decline the congestion avoiding routing will route according to the user equilibrium algorithm with good knowledge of the network.

## 3.4 Implementation in the model

As shown in **Error! Reference source not found.**, the different assumptions lead to four groups of u sers. We define four different user classes in the model, which represent the road users that are considered. These user classes represent:

1) **Habitual drivers**, who take the shortest free flow route and stick with that;
2) **Influenced drivers**, who are influenced by route guidance, but don't always follow it;
3) **Completely compliant drivers**, who follow the route guidance;
4) **Social drivers**, who are willing to take socially beneficial routes (system optimum).

Each group has its own route choice behaviour. The first group of users are the habitual drivers and they are not influenced by traffic information. Their routes are the shortest routes based on free flow travel time. For this group, the time penalty is not included (user class 1). The second group gets their information from service providers that act independently. Because a service provider represents a group of individual vehicles, there is some information available about the current traffic state. Normally, for θ a value of 1 is used, if travel times (min) are not too large (Mede & Van Berkum, 1993). But, because information is more available nowadays , for the θ parameter a value of 2 is chosen (user class 2 – see previous MARPLE description). The third group only considers their travel time and uses the data of the intermediary to achieve this (user class 3). This means that there is no time penalty included and the θ parameter is higher than this parameter for the first group (θ is 10). The final group of users will avoid congestion (user class 4). Therefore, a time penalty is added for routes with (nearly) congested links. The size of this time penalty is a percentage of the travel time, determined by the simulation. This group is connected with the intermediary and shares data, which means that the quality of traffic information is increased and is almost perfect. Therefore, the θ parameter for this group has relatively high value and is also set to 10. This value was also used in another study of route guidance during a tunnel closure (Taale, 2020).

## 3.5 Algorithm for compliance

Depending on the strategy scenario, different distributions of these user classes can be assumed to be present in a network. Not every road user is willing to accept a social route like the congestion avoiding approach. Initially, about 80% of the drivers are willing to accept it and this decreases to below 40% when the additional travel time increases (Bonsall & Joint, 1991; Mariotte et al., 2021).

 

Recent studies show that social demographic attributes have an influence on compliance (Mariotte et al., 2021; van Essen, van Berkum & Chorus, 2020). However, in macroscopic simulation, these attributes are not taken into account. A variable that will be considered is the number of participants. In general, if drivers have the feeling that others make the social choice, they are more willing to accept the social alternative. For the algorithm to determine the compliance rate, the results of two studies (Bonsall & Joint, 1991; Mariotte et al., 2021) are combined. In (Bonsall & Joint, 1991) two relations are derived between additional travel time and compliance rate: one for poor advice and one for perfect advice. It is assumed that a poor advice leads to a participation rate of 10% and perfect advice to 100%.

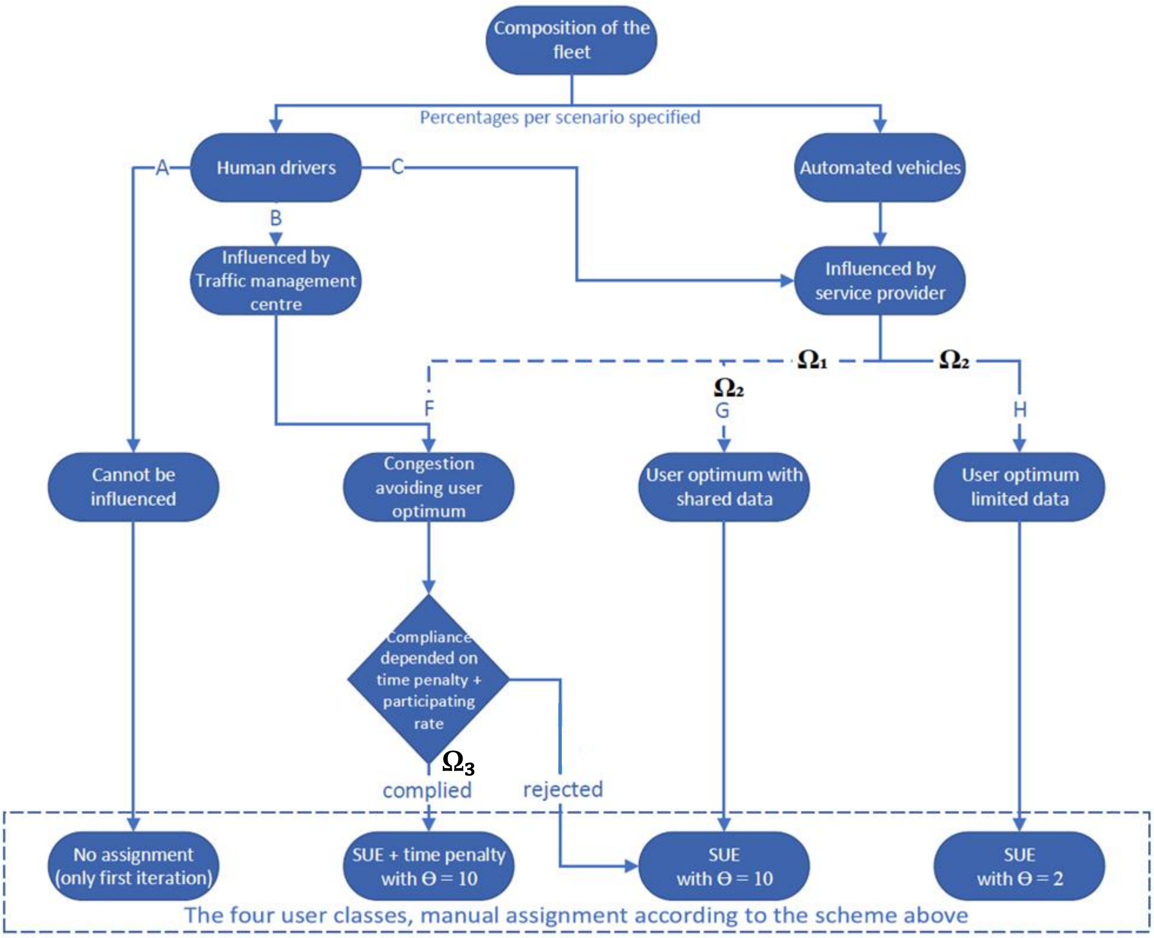


*Figure 4. Scheme for assigning traffic to specific groups of routing behavior*

Based on these results, the following equations were derived, which are used to determine the distribution of drivers/vehicles over the user classes. In these equations, C is the compliance rate (percentage), p is the participation rate (percentage) and t is the time penalty (percentage of original travel time).

Equation 1 shows the compliance function for participation rates up to 10%:

$$C = 20 + 65 * 0.97^{t} \tag{1}$$

$$Domain: \{p \geq 0 | p < 10\}$$

The compliance function for the participation rate of 100% is given by:

$$C = 35 + 50 * 0.9925^{t} \tag{2}$$
$$Domain: \{p = 100\}$$

The compliance function for participation rates between 10%-100% ,which is a transformation from equation (1) to equation (2), is then given by:

$$C = 20 + 15\frac{p-10}{90} + \left(65 - 15\frac{p-10}{90}\right) * (0.97 + 0.0225 * \frac{p-10}{90})^{t} \tag{3}$$
$$Domain: \{p \geq 10 | p < 100\}$$

Note that for p=10 equations (1) and (3) give the same results. Equation (2) follows immediately using p=100 in equation (3).

# 4 Case study

## *4.1 Network*

The considered network for the case study is a representation of the network of Milan. The network consists of 841 links (±641 km), 381 nodes and 25 zones. The OD table consists of 602 OD pairs with demand for 22 15-minutes periods (±112.000 trips), representing a broad morning peak period. It was derived from a static model and made dynamic in such a way that congestion occurs on several routes to the city (see Figure 5). The initial network came pre-calibrated for daily traffic. Further calibration of the network was performed through a process of determining suitable levels of congestion through expert judgement to let the model be able to test principles of rerouting over the network. Suitable levels of congestion were deemed to be present when congestion occurs and resolves, while not resulting in grid-locking or extended periods of unrealistically large congestion. To demonstrate the principles in this paper, it was not necessary to calibrate beyond this using additional traffic counts. As an existing demo network, it was primarily chosen for its structure for the proof of concept. A ring-structured network was assumed to be very suitable for this study, because it provides multiple route options for many origin-destination pairs. This makes rerouting possible and non-congested route alternatives more likely to exist, hence the choice for this network.

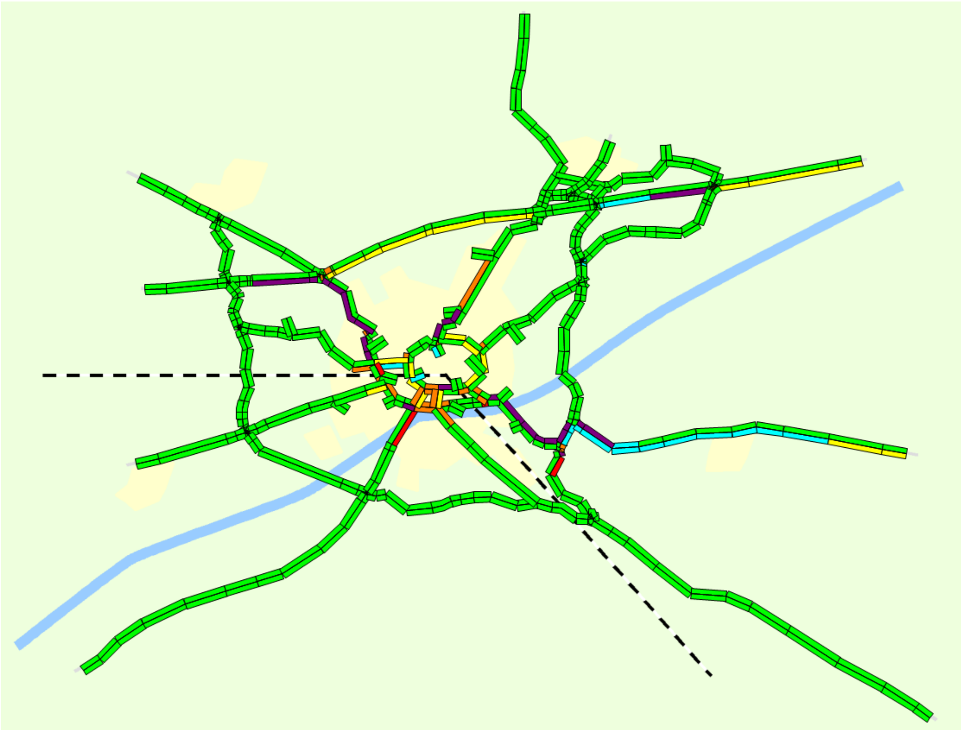

*Figure 5. Milan network (traffic situation at 9 AM, purple means severely congested)*

## 4.2 Scenarios

Four policy strategies are considered. However, for one strategy the resulting outcome in practice is not clear, as we will explain. In policy strategy $\Omega_1$, 'regulated intermediary and free of obligations', three situations can occur. The first is that the data is only shared and the service provider's use is for their own benefit. The second one is that only a part of the service providers will participate. The third situation is that every service provider uses the service voluntarily. That last situation is the same as the policy where all service providers are forced to use the services of the intermediary. Therefore, in practice there are eventually five **strategy scenarios**:

1) Do nothing;

2) A regulated intermediary, free of obligations, only used for data sharing;

3) A regulated intermediary, free of obligations, partial commitment;

4) Obligated use of intermediary services, but voluntary use for road users;

5) Obligated use of intermediary services and mandatory use for road users.

For every strategy scenario, a distribution for the different user classes in the model is calculated for different penetration rates of CAVs. For the time penalty, values are chosen based on simulations for the first user class distribution with a time penalty between 0% and 40%. Test runs showed that the optimal solution is included in this range. The time penalty with the best results is used for the other user class distributions. Furthermore, for each strategy scenario, we also consider the percentage of CAVs that are assumed to demonstrate perfect compliance with route advice. That means that with increasing percentage of CAVs the percentage of habitual drivers is decreased and these drivers are distributed among the user classes 2, 3 and 4, using equations (1)-(3), dependent on the strategy scenario. We consider steps of 10% from 0% up to 100% with assumed full compliance. The inputs for simulation scenarios are presented in Table 1.

A time penalty is added to the normal travel time for congested links. This time penalty is determined by the flow-capacity ratio. When this ratio rises above a certain threshold, the time penalty is added. Three choices for the threshold were tested in advance: 90%, 95% and 99%. The 95% threshold gave the best results, as the 90% option left too much capacity unused and the 99% resulted in excessive congestion, because flows are not completely consistent and the link could be wrongfully denied a time penalty. Other values of the penalty threshold were not tested, because these 3 options seemed reasonable choices. The second choice is the number of extra iterations simulated after the time penalty is added. For this study, it is assumed that the iteration process continues until convergence is reached. This choice is motivated by the fact that the intermediary has good information about the network state and could instruct all vehicles to use the best route. Convergence is assumed if the maximum change in route flows stays below a certain percentage. In this study, this value is set to 1%, which is a balance between the amount of traffic still changing routes (less than 1%) and the simulation time. Theoretically, the relative duality gap is a better convergence criterium. However, we found that this didn’t lead to a very different (stochastic) equilibrium. We tested this by running assignments for the Milan network using the flow criterium and calculating the adaptive relative duality gap (DG) as defined by Bliemer *et al. (58)*. Using a maximum change in route flows of less than 1% as convergence criterium, after 16 iterations the assignment reached that level. The accompanying DG was 0.0030. To see if more iterations would make a difference, we extended the assignment to 100 iterations. For that run, the resulting maximum difference in route flows was 0.02% and the DG 0.0027. Comparing the resulting route flows after 16 and 100 iterations, the sum of the difference in route flows for all routes and time periods was 0.17% of the total demand. Between those assignments, the difference in total delay was 0.3%. For practical applications and also this study, this is acceptable and will not change the conclusions.

**Table 1. Strategy scenarios and user class setting for the model**

**Scenario 1** Do nothing

| CAV % | Time penalty | user class share [%] 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0% | 10% | 70 | 20 | 3 | 7 |
| 10% | | 63 | 28 | 3 | 6 |
| 20% | | 56 | 36 | 3 | 5 |
| 30% | | 49 | 44 | 2 | 5 |
| 40% | | 42 | 52 | 2 | 4 |
| 50% | | 35 | 60 | 2 | 3 |
| 60% | | 28 | 68 | 1 | 3 |
| 70% | | 21 | 76 | 1 | 2 |
| 80% | | 14 | 84 | 1 | 1 |
| 90% | | 7 | 92 | 0 | 1 |
| 100% | N/A | 0 | 100 | 0 | 0 |

**Scenario 2** A regulated intermediary, free of obligations, only used for data sharing

| CAV % | Time penalty | user class share [%] 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0% | 10% | 70 | 0 | 23 | 7 |
| 10% | | 63 | 0 | 31 | 6 |
| 20% | | 56 | 0 | 39 | 5 |
| 30% | | 49 | 0 | 46 | 5 |
| 40% | | 42 | 0 | 54 | 4 |
| 50% | | 35 | 0 | 62 | 3 |
| 60% | | 28 | 0 | 69 | 3 |
| 70% | | 21 | 0 | 77 | 2 |
| 80% | | 14 | 0 | 85 | 1 |
| 90% | | 7 | 0 | 92 | 1 |
| 100% | N/A | 0 | 0 | 100 | 0 |

**Scenario 3** A regulated intermediary, free of obligations, partial commitment

| CAV % | Time penalty | user class share [%] 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0% | 10% | 70 | 5 | 12 | 13 |
| 10% | | 63 | 7 | 15 | 15 |
| 20% | | 56 | 9 | 18 | 17 |
| 30% | | 49 | 11 | 21 | 19 |
| 40% | 15% | 42 | 13 | 26 | 19 |
| 50% | | 35 | 15 | 29 | 21 |
| 60% | | 28 | 17 | 33 | 22 |
| 70% | | 21 | 19 | 36 | 24 |
| 80% | | 14 | 21 | 39 | 26 |
| 90% | | 7 | 23 | 42 | 28 |
| 100% | | 0 | 25 | 45 | 30 |

**Scenario 4** Obligated use of intermediary services, but voluntary use for road users

| CAV % | Time penalty | user class share [%] 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0% | 15% | 70 | 0 | 12 | 18 |
| 10% | | 63 | 0 | 15 | 22 |
| 20% | | 56 | 0 | 18 | 26 |
| 30% | | 49 | 0 | 21 | 30 |
| 40% | | 42 | 0 | 24 | 34 |
| 50% | | 35 | 0 | 27 | 38 |
| 60% | | 28 | 0 | 29 | 43 |
| 70% | | 21 | 0 | 32 | 47 |
| 80% | | 14 | 0 | 35 | 51 |
| 90% | | 7 | 0 | 38 | 55 |
| 100% | | 0 | 0 | 41 | 59 |

**Scenario 5** Obligated use of intermediary services and mandatory use for road users

| CAV % | Time penalty | user class share [%] 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| 0% | 25% | 70 | 0 | 0 | 30 |
| 10% | | 63 | 0 | 0 | 37 |
| 20% | | 56 | 0 | 0 | 44 |
| 30% | | 49 | 0 | 0 | 51 |
| 40% | | 42 | 0 | 0 | 58 |
| 50% | | 35 | 0 | 0 | 65 |
| 60% | | 28 | 0 | 0 | 72 |
| 70% | | 21 | 0 | 0 | 79 |
| 80% | | 14 | 0 | 0 | 86 |
| 90% | | 7 | 0 | 0 | 93 |
| 100% | | 0 | 0 | 0 | 100 |

# 5 Case study results

To show the impact of the centralized route guidance system with different regulation sets, the results from the described scenarios are presented and analysed in this section. The network performance is analysed using the Total Distance Travelled (TDT) and the Total Time Spent (TTS), which is the aggregated time of all vehicles in the network, with the condition that the number of vehicles in each scenario is identical and that the network is empty at the end of the simulation time. The TDT is shown, because rerouting traffic has an impact on that. Furthermore, the network performance is evaluated through consideration of network delays, given as percentage difference between scenarios of the aggregated delay over all vehicles and the observed queue lengths.

## *5.1 Network Performance*

Figure 6 shows the total distance travelled in the network for the five scenarios. In the figure two things attract the attention. First, the less freedom SP's and road users have in their route choice, the higher the distance travelled (scenarios 4 and 5) and second, the distance travelled decreases with higher penetration rates of automated vehicles, except for the fifth scenario, in which SP's and road users are both obligated to follow directions.

The results of the TTS for the Milan ring network (Figure 7) show that with increasing compliance and regulation, the TTS for the network is reduced. Strategy 5 (Obligatory use of intermediary and mandatory use for road users) shows an improvement compared with the base scenario of doing nothing by 0.4% for 0% automated vehicles, while an improvement of 1.1% is achieved with 100% automated vehicles. Both these numbers are substantial improvements when considering the whole network, which is an indication that the regulations improve traffic flow. We see that the current implementation of the intermediary without commitment leads to only 0.06% improvement and finally to an improvement with automated vehicles of 0.27%. It also shows that more regulation lead to better traffic performance.

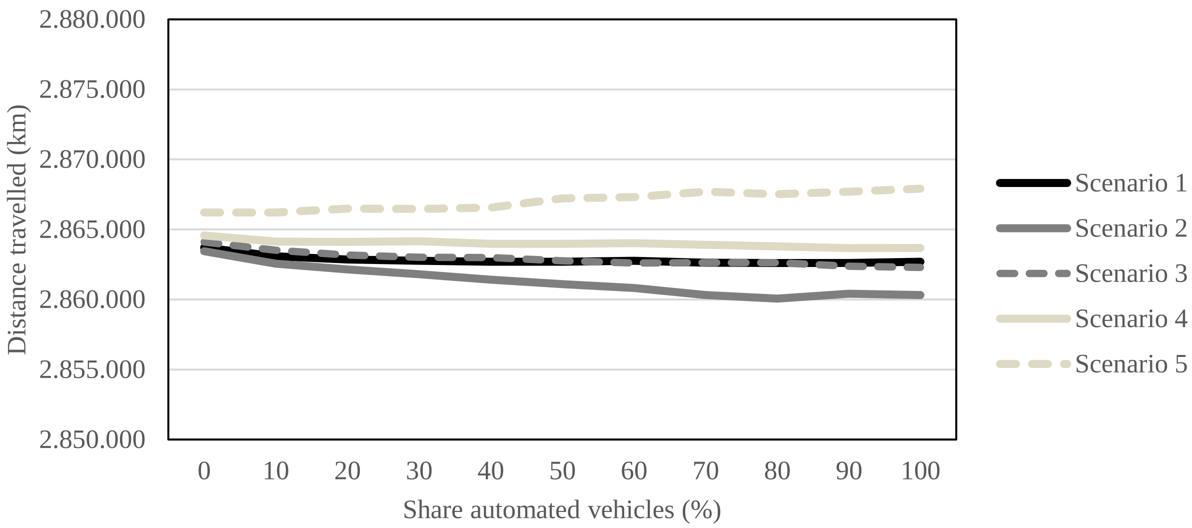


*Figure 6. Total distance travelled for the Milan ring network*

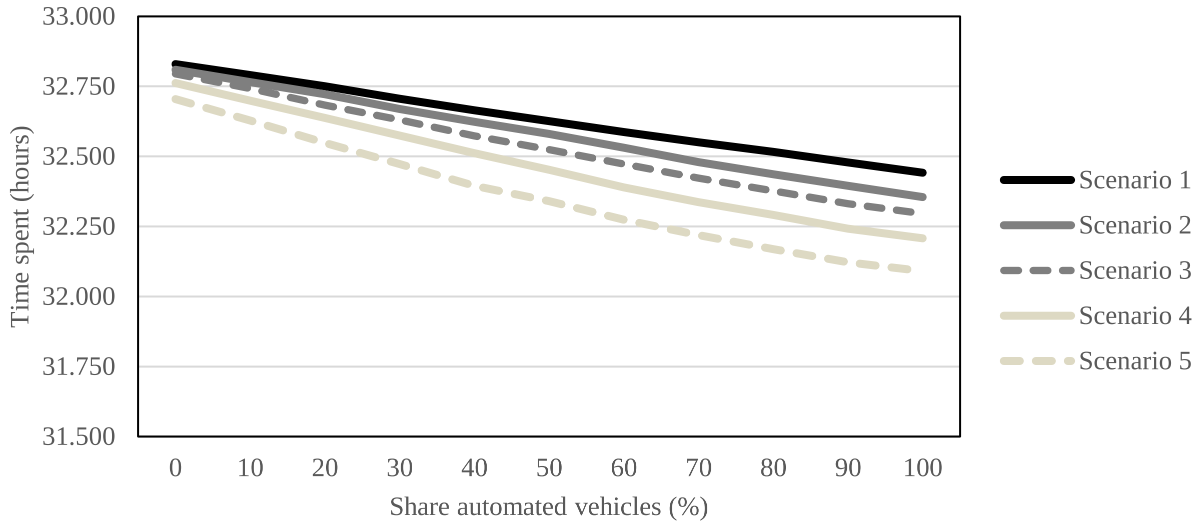


*Figure 7. Total time spent for the Milan ring network*

When this is translated to savings in delays, the total delay is reduced by 0.4%, 1.0%, 2.1% and 4.2% respectively for the strategy scenarios with 0% automated vehicles (Figure 8). With 100% automated vehicles, the delay savings increase to 1.4%, 4.1%, 7.3% and 12.5%. It should be noted that due to the complexity of the network and limited rerouting options in some places, not all congestion could be solved.

## *5.2 Sensitivity time penalty*

As the time penalty is a key variable in the analysis, we show the effects of different time penalty values with a sensitivity analysis. Figure 9. Relative effect of the time penalty per regulated scenarios

shows the relative effect of the time penalty on the total delay for selected scenarios compared with the outcome of applying no time penalty at all. A selection of scenarios is varied in the number of participants with congestion who avoid rerouting. With more participants, the optimum of the time penalty shifts towards larger time penalties and the result becomes more sensitive if the penalty is set too high. Changes to the sensitivity can be explained by the change in the actual number of vehicles that avoid congestion. If this change gets larger, the effect becomes increasingly marked as more road users switch to a user optimal route. The reason for the shift in optimal time penalty can be explained by the reason that with fewer participating vehicles the potential of the scenario is reached faster. For example, consider an ideal situation where 20% of the vehicles must make a detour to avoid congestion with a time penalty of 20%. When only 10% of the vehicles participate, congestion is not resolved. This means that the difference in travel time between the congested route and the detour route is smaller. With a smaller difference, it is beneficial to lower the time penalty to balance the volume of vehicles that change route through increased compliance.

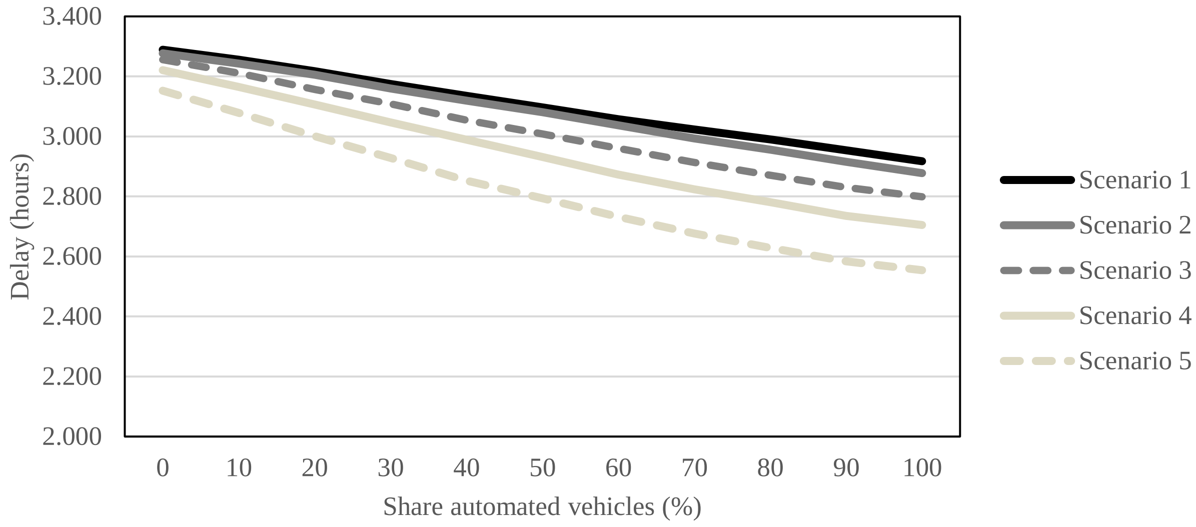


*Figure 8. Network delay*

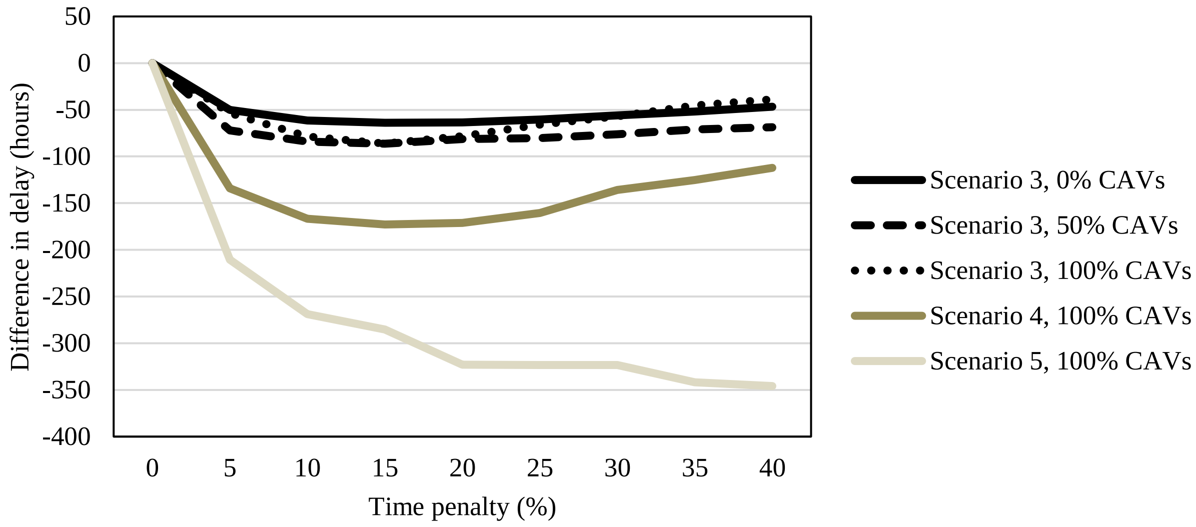


*Figure 9. Relative effect of the time penalty per regulated scenarios*

# 6 Discussion and limitations

The focus of this study is on the potential to utilize strategy policies for route guidance with different stakeholders (road authorities and private parties). The study shows encouraging results that cooperation between these stakeholders can improve traffic flow rather than be detrimental if stakeholders would be counteractive with different approaches. There remain challenges in regard to the implementation of the approach. However, the existence of the SOCRATES$^{2.0}$ project demonstrates a willingness for parties to work together and the case study here shows that it has value. It is still an open question if stakeholders can be persuaded to cooperate and how to organize that. This remains ongoing work that will follow this research effort. Based on literature, it could be expected that strict regulations for cooperation may not be required and the full potential of cooperation could be reached if all service providers participate. However, our results show that this is does not need to be the case. While network characteristics play an important role, regulation of intermediaries still yields good results with the need for obligatory involvement.

While the concept of coordination makes cooperation possible, it could lead to some undesirable side effects, especially where multiple coordination centres exist, unbundling may lead to flawed coordination (Brunekreeft, 2015). Because a country like The Netherlands has five regional traffic centres to control the highway network, this could lead to an issue in the future. As only a single region is considered in this study, flawed coordination is not a concern. Another consideration to be taken is the potential lack of competitive incentives (Jaag & Trinkner, 2011; Armstrong & Sappington, 2006). Because the intermediary takes overall network management tasks, service providers cannot compete with providing the fastest route. This may lead to a reduction of investments in the future because investments do not lead to exclusive rights to harvest the benefits of the investment.

In this study, we include and assume that the future introduction of Connected Automated Vehicles (CAV) will play a significant role in the ability to control traffic. This is based on the assumption that CAVs will show near perfect compliance. For the sake of this research, this is a suitable assumption, especially as the penetration rate of CAV in traffic is varied to allow its influence to be shown. However, we do concede that it can also be argued that full compliance will not be the case, even if that could also be potentially one option for regulators to employ if they wished. Furthermore, the presence of CAVs in this study is only considered with regard to their compliance. Any difference in vehicle dynamics are not considered to allow the main premise of stakeholder cooperation to be properly tested.

An important component of the approach is the application of the time penalty. Detours are a main part of rerouting in which drivers may perceive they have a longer detour. The perceived detour depends on the application of the time penalty. With a time penalty of 20%, no one can change route to obtain a travel time benefit of more than 20%. This means that that a specific road user will not suffer more than 30 seconds on average compared with the unregulated situation but can perceive a detour of at most 20%. Because people may dislike this, the maximum time penalty can be reduced at the expense of a slightly decreased positive impact on the system. In our case for example, a reduction of the time penalty from 15% to 10% has minimal impact on the results while the compliance of the policy may improve enough to make it acceptable for policymakers. The applied penalties are calibrated for use on the Milan ring network, however for other networks, we hypothesis that a time penalty that approaches the difference in travel time in free-flow conditions would suffice. For the impact on the traffic flow, the adjustment of the time penalty is crucial. A too large time penalty can negate time gains by offering overly long detours and can lead to a reduction of compliance. A limited reduction of the optimal time penalty can have a slight reduction to the traffic flow performance while it can have a significant impact on the support of the policy. Also, it is assumed that the compliance is constant and related to the time penalty. In reality it is possible that the compliance is also dependent on the number of re-routings, but that was not investigated. For both dependencies a sensitivity analysis is interesting, but left for further research. A limitation of the study is that only the network of Milan was simulated. Other networks could lead to other results. However, it is anticipated that networks with the similar structures (ring road) or other opportunities for route choice, will give more or less the same outcome, assuming that the approach chosen in this study is robust and not too sensitive for the assumptions on traffic assignment conditions and the time penalties applied.

In other studies, instead of a congestion avoiding algorithm a system optimum algorithm is sometimes used. A system optimum algorithm will achieve the real (modelled) optimum, instead of approaching it with the congestion optimum algorithm. For this reason, the applied algorithm can be considered to be too simplistic to investigate the maximum potential of the system. However, because a system optimum is difficult to calculate in a dynamic context and for large networks, the approach to apply a penalty to 'force' traffic to avoid congestion could be more realistic and actually resemble real traffic reactions more than an artificial system optimum, which is known to never completely exist in practice. In the simulation model, MARPLE, the concept of information for routing is supported by literature (Mede & Van Berkum, 1993) and the idea of changing theta as a parameter to distribute traffic over alternative routes is plausible. If we consider the case of little available information for road users, the chance of choosing the slower route becomes more likely. A shortcoming of a macroscopic DTA model like MARPLE is the omission of the capacity drop. While not unusual in macroscopic models, it has an impact especially where congestion is present. With capacity drop present, the impact of the strategy to avoid congestion could have been larger.

# 7 Conclusions

Route guidance has the potential to improve network performance and traffic flow, however counteractive approaches by Road Authorities and Service Providers (SP) can be detrimental to this. Cooperation between the two has the potential to get the best out of the measure by utilising a System Optimum approach, while still allowing SPs to offer individual travel advice. In this paper, we have shown the potential impacts of different policy strategies for collaboration between RAs and SPs. Cooperation ranges from regulation of SPs, with and without obligation to cooperate, to full mandatory cooperation and enforcement of specific route guidance advice. Additionally, various levels of user compliance are considered, including mandatory and voluntary compliance options and the investigation of the potential of connected automated vehicles with full compliance to influence performance.

The results of a modelled case study of the Milan network clearly show that both far-reaching cooperation and increased compliance have a positive effect on traffic network performance in terms of reduced delays, reduced congestion and total time spent (even with rerouting). A comparison is made against a ‘do nothing’ reference scenario in which SPs offer user optimal advice and RAs recommend system optimal advice. Even with some regulation and without obligation to participate, improvements in performance are experienced in network performance of a few percent in most indicators. While full obligation for SPs to provide system optimum advice and full compliance does offer significant network performance improvements, potentially ranging about 10% for some indicators, this may be unrealistic to expect this level of cooperation in the future. Nevertheless, the study has demonstrated the potential benefits of any form of cooperation and therefore come with a strong recommendation for road authorities and service providers alike to continue to seek for cooperation to aid traffic performance in the future.

A final aspect of this research considered the impact of fully compliant connected automated vehicles. This showed that with increasing percentage of CAVs with complete compliance, that route guidance can have a substantial positive effect compared to less compliance or a smaller penetration rate of automated vehicles. With this comes the recommendation for authorities and car manufactures alike to consider the positive effects of full cooperation and compliance as CAVs continue to make ground in terms of capabilities and market share.

Further research could involve other networks and other demand patterns. The case studied had a certain structure with sometimes limited route options. Other cases with more (or less) route choice options or different demand patterns could give other results. Also, future work following this paper should be focussed on considering other aspects of how automated vehicles may influence traffic management further in the future, and could focus on emissions reduction as the optimisation target, rather than only traffic performance.

## *Contributor Statement*

The authors confirm contribution to the paper as follows: study conception and design: B.D. van den Burg; model development: H. Taale; analysis and interpretation of results: S.C. Calvert, B.D. van den Burg, H. Taale; draft manuscript preparation: S.C. Calvert, B.D. van den Burg, H. Taale. All authors reviewed the results and approved the final version of the manuscript.

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