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Assessing the travel impacts of subnetworks for automated driving: An exploratory study

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ABSTRACT

This study explores a network configuration concept for vehicle automation levels 3–4 (according to SAE classifications) in an urban road network having mixed traffic and demonstrates its potential impacts. We assume automated driving will be allowed on a selection of roads. For the remaining roads, manual driving (although supported by assisting driving automation systems) will be compulsory. Accordingly, we introduce an approach for road selection and present relevant operational concepts. To evaluate the impacts of this configuration and model different vehicles' route choice behavior in mixed traffic, a static multi-class stochastic user equilibrium traffic assignment with a path-size logit route choice model and a Monte Carlo labeling route-set generation is adapted. Two user-classes are distinguished: vehicles with automation levels 0–2 and vehicles with automation levels 3–4 having a different passenger car unit to account for lower driving headways, lower value of time, and higher fuel efficiency. The results indicate a decrease in total travel cost with the increase in market penetration rate of higher automation levels, a decrease in total travel time, and a minor increase in total travel distance. Although in most cases vehicles with higher automation levels benefit more from the improvements, no deterioration in travel conditions is observed for the rest of the vehicles in any scenario. Furthermore, a noticeable shift of traffic from roads with access function to roads with flow function and distributors is observed. Sensitivity analysis shows that the extent of changes in the impacts is not strongly dependent on the input parameters.

1. Introduction

With recent technological and strategic advancements in automobile industries and transportation sectors, there are new possibilities for the future of mobility. Automated driving (AD) is one of the promises of the future. According to (SAE International, 2016), there are five levels of vehicle automation; at levels 1–2, the driving automation system provides the driver with longitudinal and lateral control (i.e., adaptive cruise control and lane keeping). Such technologies are already available in the automobile market and they can operate on existing infrastructure. At level 3, automated driving system (ADS) monitors the environment and executes driving tasks on certain operating design domains (ODD) (e.g. driving in motorways), allowing the drivers to avert their attention from driving tasks while being ready to take back control in case of a failure in ADS or approaching situations beyond ODD of level 3 ADS (i.e., difficult driving conditions that level 3 ADS is unable to handle). Level 4 ADS is expected to handle the fail-safe situation autonomously; however, the ODD would still be limited. This means that levels 3–4 might require dedicated infrastructure or roads with specific requirements. Finally, at level 5, ADS is expected to be feasible for all driving modes and completely self-sufficient. This last level of automation signals a major evolution in the prospect of mobility, but it is not expected in the near future (Shladover, 2016).

AD is a trend that will evolve over time, both in the level of automation and the market penetration rate of automated vehicles (AVs). Many studies focus on the impacts of AD for the case that the total fleet is fully automated (SAE level 5 with unlimited ODD); however, it might take a long time before this situation is realized. In the transition period, there will be a mix of different levels of automation, including level 0 (i.e., non-automated vehicles). According to (SAE International, 2016), ODD of levels 3–4 ADS is limited. That means vehicles equipped with ADS at these levels cannot drive in automated mode everywhere. The question of where can levels 3–4 automated vehicles drive safely in automated mode has not received enough attention in the academic literature yet. Furthermore, this can have implications for the usage of transport networks and travel choices.

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For AD levels 3–4, we envision that automated driving will be allowed on a selection of roads and for the remaining roads, manual driving will be compulsory (albeit supported by various assisting driving automation systems such as collision avoidance systems). In these selected roads, automated driving will be allowed in mixed traffic conditions (i.e., in the same lanes with none-automated vehicles) and these roads need investments to fulfil certain design requirements to facilitate safe and efficient AD. There is therefore a need for a network design approach to decide which roads should be selected to facilitate AD levels 3–4 in the transition stage.

The aim of this paper is to explore the concept of a specific network configuration for AD levels 3–4 and to estimate its impacts on travel time, distance and cost in urban regions having mixed traffic. Network configuration refers to the selection of links on which levels 3–4 AD is facilitated.

Our focus is on network configuration concepts and their impacts on route choice behavior and consequently, on generalized travel cost. Yet, it should be noted that AD can have several impacts on travel choices including location, destination, mode, departure time, and route choice as well as driving behavior. For an extensive review of existing literature on impacts of AD, the reader is referred to (Milakis et al., 2017).

We introduce the concept of AD subnetwork as a possible network configuration for the transition period, elaborate on our approach for link selection, and explain relevant operational concepts. In order to evaluate network usage and route choice impacts of this configuration, we introduce a modified static multi-user class (MUC) stochastic user equilibrium (SUE) traffic assignment method with a path-size logit as well as a Monte Carlo labeling combination approach for a priori route set generation. Then, we present a case study to demonstrate the concept of AD subnetwork, and we analyze its impacts on a specific network.

Based on this analysis and an exploratory literature study, we present a research agenda for the development of a network design method to accurately model and assess the impacts of various network configurations for AVs in urban regions.

The rest of this manuscript is organized as follows: section 2 explains the problem background and an explorative literature study; section 3 introduces the concept of AD subnetwork and our evaluation method; section 4 presents the case study and numerical results; and the last two sections present discussion, conclusion, and recommendations.

2. Background

In order to provide a systematic discussion on the literature, we categorize relevant studies into three major clusters, namely, microsimulations, macro simulations, and network design problem (NDP). Since this is an exploratory study, and there is no other study in the literature that addresses our problem with the same method, we do not place our work within any of these classes. Instead, we refer to the most relevant studies in each category and mention their common aspects with our study with the aim of positioning our work within the literature.

2.1. Microsimulations

One of the major envisioned advantages of AD is the possibility of cooperative adaptive cruise control (CACC). Shladover et al., (2015) provide clear definitions and operating concepts of CACC. yMain benefits of adaptive cruise control (ACC), i.e., improving traffic flow and fuel efficiency, are expected to be realized with cooperative ACC (CACC) rather than autonomous ACC. CACC with vehicle to vehicle (V2V) communication could reduce the average driving time headway from 1.4 s (current average for manual driving) to approximately 0.6 s (Nowakowski et al., 2010) which would increase lane capacity. With reduced time headways, at 100% penetration rate of CACC-equipped vehicles, it is possible to increase lane capacity in motorways without bottlenecks from 2200 v/h to about 4000 v/h (Shladover et al., 2012). Using the microscopic MIXIC traffic simulation model of a highway bottleneck, (van Arem et al., 2006) conclude that CACC has the potential to improve traffic stability and throughput depending on market penetration rate and traffic volume. The extent of positive impacts becomes greater with higher penetration rates ($>60\%$) and higher traffic volumes.

Several microsimulation studies consider dedicated lanes for CACC-equipped vehicles. Using the MIXIC simulation model on a four-lane highway, (van Arem et al., 2006) conclude that only with high CACC penetration rates for the highway stretch before the bottleneck with high traffic volume, the case with dedicated CACC lane has a better performance compared to the case without the special lane. However, in the scenario with 20% CACC penetration, severe congestion is observed before the lane drop. By means of a microsimulation framework including varying behavioral mechanisms for connected and automated vehicles, (Mahmassani, 2016) concludes that dedicated lanes for AVs can only be effective if their use is optional and when the market share of AVs is larger than the percentage of nominal capacity represented by that lane.

Microsimulation experiments are flexible tools to study local and specific impacts of AVs under different scenarios using various micro models. However, existing studies focus on specific stretches of motorways. To the best of our knowledge, there is no published microsimulation study on urban streets. Moreover, they are infeasible for network-wide studies.

2.2. Macro simulations

An alternative approach for assessing the impacts of AD at network level is to use macroscopic traffic assignment models. Some researchers have used the expected impacts of AD from the literature along with certain behavioral assumptions for AVs to develop macroscopic models to study their impacts on transport networks. Many studies conclude that deployment of CACC leads to faster reaction times, thereby reducing driving time headways which can increase lane capacity (see, for instance (Shladover et al., 2015; Nowakowski et al., 2010; Shladover et al., 2012; van Arem et al., 2006; Mahmassani, 2016). In a macroscopic static traffic assignment, this can be modeled via lower passenger car unit (PCU) values or higher link capacities. The magnitude of this change depends on the proportion of AVs on the link and is reported for several future scenarios in (Puylaert et al., 2017) where the authors use a system dynamic approach to quantify the impacts of early forms of automation. Another expected impact from CACC is fuel efficiency (Shladover et al., 2015; Shida and Nemoto, 2009; Rios-Torres and Malikopoulos, 2017). This can be included in generalized travel cost used in macroscopic traffic assignment models via value of distance (VoD). Additionally, value of time (VoT) might change in parts of the trips where AD is possible. Although there is no consensus in the literature about the effect of AD on VoT, some studies conclude that the possibility of performing other activities in AVs might lead to lower VoT (Puylaert et al., 2017; Milakis et al., 2017). These expected effects suggest that AVs could be modelled as a separate user class.

(Levin and Boyles, 2015) present a multi-class four-step model using a static traffic assignment that includes AV repositioning to avoid parking fees, increases in link capacity as a function of proportion of AVs, and several classes in demand based on VoT and AV ownership. The study focuses only on the differences between no automation and full automation (i.e., level 0 and level 5 SAE). A multiclass cell transmission model (CTM) is developed in (Levin and Boyles, 2016) to model the differences in capacity and backward wave speed in shared conventional vehicle (CV) and AV roads. This model is used in (Patel et al., 2016) to study the effects of reservation controls and increased capacity from AVs on highway and arterial networks.

2.3. Network design problem

In transportation literature, optimal decisions regarding adjustments to and expansions of road network infrastructure are considered within the concept of NDP (Yang and Bell, 1998). So far, very few studies have proposed new network configurations for AVs and considered them within the concept of NDP. (Chen et al., 2016) consider the problem of optimal deployment of AV lanes as a bi-level NDP where the upper level includes decisions such as where, when, and how many lanes should be considered as dedicated lanes for AVs and the lower level includes network equilibrium with two classes representing CVs and AVs. The study presents a possible network configuration for AD, and a network-wide assessment of its impacts using a macroscopic static traffic assignment with an MUC deterministic user equilibrium (DUE) route choice model.

Another network configuration is presented in (Chen et al., 2017) where the authors consider the problem of optimal AV zones in transport networks. An AV zone includes links that are adjusted for AVs. CVs are not allowed in AV zones. So, different classes of vehicles encounter different network topologies. As for routing, they consider a deterministic mixed routing model where system optimal routing is applied for AV zone and user equilibrium for the rest of the network.

2.4. An alternative network configuration

So far, the only studies considering AD concepts in NDP and offering specific network configurations are (Chen et al., 2016) and (Chen et al., 2017). A possible improvement on both studies is considering a clear definition of AVs (i.e., their automation level) as well as their ODD. Furthermore, in order to apply these methods in practice, some extensions to their network representation are necessary to consider various road types in urban settings.

This paper offers a more realistic network configuration compared to dedicated lanes and AV zones for the transition period. We select certain parts of the network mainly consisting of roads with flow and distribution function to allow for AD (road functionality is discussed in the next section). Adjustments to these roads include (but are not limited to) improvements in quality of on/off ramps, lane markings, road and traffic signs as well as rearranging intersections with uncontrolled complex conflicts and separating inhomogeneous traffic. For an overview of possible adjustments the reader is referred to (Zhang, 2013; Courbon, et al., 2016; Nitsche et al., 2014; Farah et al., 2018). These adjustments can improve safety for all road users, regardless of market penetration rate of AVs and development path of AD in the future.

Therefore, the problem becomes choosing links to adjust in order to construct a subnetwork to allow and facilitate AD in mixed traffic. This study presents a qualitative scheme for this selection. For assessing the first-order impacts of rerouting in this configuration, a modified MUC static stochastic traffic assignment model is utilized. The modifications are based on the expected impacts of AD from the literature which was discussed earlier in this section and will be elaborated on in the next section.

3. AD subnetwork

In this section, we introduce and elaborate on the concept of AD subnetwork. Furthermore, we propose a model to evaluate the performance of this configuration. Mathematical formulation and the solution method for this model are discussed in this section as well.

3.1. Constructing the AD subnetwork

In order to envisage a network configuration for AD, it is essential to specify a feasible realm of operation for ADS levels 3–4. Four major criteria are considered in defining the feasibility of roads for AD; roads with limited access, high quality (e.g. pavement, lane marking, traffic signs, and lights), segregated traffic (homogeneity of mass and speed for vehicles in each lane), and grade separated or clear at-grade intersections are regarded as feasible. Additionally, roads with potential for having such standards with reasonable adjustments are added to the set of feasible links. Adjustment costs and optimizing the link choice set are not included in this study but debated in the discussion.

Network hierarchy and road function are defining factors for road standards and their potential for accommodating AVs mixed with CVs carrying the least possible risk of conflicts. The categorization of roads based on their function was first introduced in (Buchanan, 1963). Later this became the basis for mono-functionality principle of sustainable safety vision in the Netherlands (Wegman et al., 2008; Wegman and Aarts, 2006). The principle entails that roads must have a single function and their design and use should comply with that function. Facilitating traffic throughput (mobility or flow function) and providing access to destinations (accessibility or access function) are two possible road functions. Distribution function is a third category introduced to offer the appropriate transition between providing access and facilitating throughput. Although finding a clear correspondence between road function and network hierarchy is not always a straightforward task, freeways mainly serve mobility by facilitating throughput (flow function) and most local roads serve accessibility by providing access to adjacent parcels (access function). It should be noted that roads are not always designed to serve a single function.

Road network observations in Delft, the Netherlands reveal that all roads with flow function and the majority of roads with distribution function (potentially) meet mentioned standards. In contrast, none of the roads with access function meets the standards. Then the process is reduced to approving roads with flow function, rejecting roads with access function and examining the distributors to specify AD subnetwork. Fig. 1 (the case study section) depicts the constructed AD subnetworks for the case of Delft which is discussed in details later in this paper.

Fig. 1. AD subnetwork variants (from left, respectively): variant 3 (main variant), variant 2, and variant 1 (links that belong to the AD subnetwork are shown with (bright) green and the rest with (dark) blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. Operational concepts and assumptions

Our assumptions regarding the AD subnetwork concept and how it is used by CVs and AVs are summarized below:

- Levels 3–4 ADS-equipped vehicles (AVs) form CACC platoons (whenever possible) in automated mode only within the AD subnetwork and this concept is referred to as automated driving (AD);
- Levels 0–2 vehicles (CVs) do not form CACC platoons and AD is not possible for them, although they can use assisting driving automation systems which should not be confused with ADS;
- AVs always start manually and proceed in manual driving mode till reaching AD subnetwork (green parts in Fig. 1);
- Upon arrival to AD subnetwork, the ADS notifies the driver of the possibility of AD and the driver opts for AD;
- When reaching one of the boundaries of the AD subnetwork, ADS notifies the driver again to take back control and resume manually;
- The driver must be ready at all times to take back control, particularly when exiting AD subnetwork and in case of a failure in level 3 ADS;
- Outside the AD subnetwork (blue parts in Fig. 1) all vehicles drive manually;
- All vehicles are allowed everywhere in the network but AD is only possible inside the AD subnetwork for AVs.

3.3. Multi-class route choice and network equilibrium

Modeling AVs' routing behavior within the AD subnetwork requires considering the effects of AD on generalized travel cost, which is the determining factor for route choice. The main expected effects of AD levels 3–4 on generalized travel cost are capacity improvements via shorter headways, lower VoT through the use of time for other activities in AVs, and lower VoD due to fuel efficiency of CACC. We adopt a generalized travel cost function consisting of the summation of distance weighted by VoD, and travel time weighted by VoT (Eq. (13)). On the links within the AD subnetwork, lower VoD and VoT values are applied for AV class (Eq. (14)). Link travel time is based on a modified BPR function where total flow is a weighted sum of class-specific flows to capture the correlation between link capacity and the proportion of AVs on the link (Eq. (7)). Weighting is based on PCU values. Lower PCU values are applied for AVs on links within the AD subnetwork to account for the shorter gaps between AVs and their leading vehicles (Eqs. (2) and (3)). The magnitude of changes in PCU, VoD and VoT are reported in Table 1 and discussed in the next section.

We argue that for the transition period, system optimal route choice is highly unlikely, therefore the most realistic approach to frame the network equilibrium problem is an MUC SUE formulation. Fisk (1980) presents the formulation of the single class logit-based SUE assignment as a mathematical programming problem. An early extension of the problem to an MUC SUE is introduced by Daganzo (1983). Most common formulations of the SUE problem are based on the multinomial logit (MNL) model due to its closed form and efficient computation times. However, the known issue of independence of irrelevant alternatives (IIA) in MNL models can lead to overestimation of flow for overlapping routes. Several extensions to the MNL model have been discussed in (Chen et al., 2012) where the performance of existing extensions to the MNL model are compared. The path-size logit (PSL) model presented by Ben-Akiva and Bierlaire (1999) is one of the extensions that can lead to more realistic flow predictions. In this study, an MUC extension of PSL SUE formulation is presented. Different formulations for PSL are reported in the literature. The one adapted here is based on the formulation introduced in (Ben-Akiva and Ramming, 1998). The mathematical formulation of this method is presented in the next subsection. Our main modeling assumptions for route choice are summarized below:

- Route choice is based on an MUC SUE where within the AD subnetwork, AV class has a lower generalized travel cost due to lower VoT and VoD resulting from CACC, but in the remaining parts of the network all classes have identical generalized travel cost;
- Link travel time within the AD subnetwork depends on the proportion of AVs. A weighted sum of class-specific flows based on their PCU value is used to calculate link travel time (Eqs. (2), (3) and (7)).

Table 1
Important input parameters related to AD for Delft case study.

Parameter	Class	Penetration rate		Bandwidth (sensitivity analysis)
		[0%-40%]	[40%–100%]	
PCU	CV	1	1	–
	AV	0.95	0.9	[0.7–1.1]
VoT (€/h)	CV	9	9	–
	AV	8.55	8.55	[6.3–9.9]
VoD (€/km)	CV	0.19	0.19	–
	AV	0.18	0.16	[0.13–0.21]
μ	CV	0.2	0.2	–
	AV	0.29	0.29	–
β	CV	3	3	–
	AV	3	3	–

3.4. Mathematical formulation

The following notation is used throughout this paper.

W = Set of origin − destination pairs w

R^w = Set of routes r between origin − destination pair w

M = Set of user classes m

A_0 = Set of links a not belonging to AD − enabled subnetwork

A_1 = Set of links a belonging to AD − enabled subnetwork

A = Set of all links a in the network; $A_0 \cup A_1$

μ_m = Logit choice model parameter for class m

D_m^w = Demand of origin − destination pair w for class m

$PS_m^{w,r}$ = Path − size penalty of route r between origin − destination pair w for class m

β_m = Path − size correction parameter for class m

η_m = Value of time for class m

t_a^0 = Free flow travel time of link a

θ_m = Driving cost per kilometer for class m (VoD)

l_a = Length of link a

γ_m = PCU value of class m

$\delta_{m,a}^{w,r}$ = 1 if flow of w from route r for class m uses link a, 0 otherwise (assignment map)

α_a = BPR function parameter for link a

b_a = BPR function parameter for link a

Λ_a = Capacity of link a

$t_a(q_a) =$ *Travel time of link a*

$q_a =$ *Total flow of link a based on weighted sum of class − specific flows (PCU equivalent)*

$F_m^{w,r} =$ *Flow in route r between O − D pair w for class m (class − specific route flow)*

$f_{m,a} =$ *Flow in link a for class m (class − specific link flow)*

$C_m^{w,r} =$ *Travel cost of route r between O − D pair w for class m (route cost)*

$c_{m,a} =$ *Travel cost of link a for class m (link cost)*

$\bar{f}_{m,a} =$ *Equilibrium flow of class m in link a*

$\bar{t}_a =$ *Equilibrium travel time of link a*

$P_m^{w,r} =$ *Proportion of travelers of class m taking route r between O − D pair w*

$TTC =$ *Total travel cost*

$TTT =$ *Total travel time*

$TTD =$ *Total travel distance*

3.4.1. Traffic assignment: network equilibrium

Our PSL-based MUC SUE formulation for route choice is presented here as a mathematical programming problem.

MP:

Minimize

$$Z = \sum_m \frac{1}{\mu_m} \sum_{w\in W} \sum_{r\in R^w} F_m^{w,r} \ln F_m^{w,r} - \sum_m \frac{1}{\beta_m} \sum_{w\in W} \sum_{r\in R^w} F_m^{w,r} \ln PS_m^{w,r} + \sum_{m\in M} \sum_{a\in A} \int_0^{q_a} c_{m,a}(x)dx, \tag{1}$$

s.t.

$$q_a = \gamma_0(f_{0,a} + f_{1,a}), \quad \forall\, a \in A_0, \tag{2}$$

$$q_a = \gamma_0 f_{0,a} + \gamma_1 f_{1,a}, \quad \forall\, a \in A_1, \tag{3}$$

$$\sum_{r\in R^w} F_m^{w,r} = D_m^w, \quad \forall\, w \in W, \forall\, m \in M, \tag{4}$$

$$\sum_{w\in W} \sum_{r\in R^w} F_m^{w,r} \delta_{m,a}^{w,r} = f_{m,a}, \quad \forall\, a \in A, \forall\, m \in M, \tag{5}$$

$$F_m^{w,r} \geqslant 0, \quad \forall\, w \in W, \forall\, m \in M, \forall\, r \in R^w. \tag{6}$$

First equation introduces the objective function with three terms: the first one maximizing the entropy of flows leading to stochastic route flows, the second one including the path-size penalty for overlapping routes, and the third term minimizing individual generalized travel costs. Eqs. (2) and (3) introduce the PCU equivalent of total flow as a PCU-weighted sum of class-specific flows which is used in calculating link travel time. Eq. (4) guarantees total route flows satisfy total demand, and Eq. (5) converts route flows to corresponding link flows for each class. Link travel time function is given as:

$$t_a(q_a) = t_a^0 \left[1 + \alpha_a \left(\frac{q_a}{\Lambda_a}\right)^{b_a}\right]. \tag{7}$$

And link cost per class is:

$$c_{0,a}(q_a) = \theta_0 l_a + \eta_0 t_a(q_a) \quad, \ \forall\, a \in A, \tag{8}$$

$$c_{1,a}(q_a) = \theta_0 l_a + \eta_0 t_a(q_a) \quad, \ \forall\, a \in A_0, \tag{9}$$

$$c_{1,a}(q_a) = \theta_1 l_a + \eta_1 t_a(q_a) \quad, \ \forall\, a \in A_1. \tag{10}$$

Eqs. (9) and (10) guarantee different link travel costs for AV class within and outside the AD Subnetwork using different VoT and VoD values. The solution to the above MP formulation gives the following probability for route proportions:

$$P_m^{w,r} = \frac{\exp(-\mu_m C_m^{w,r} + \beta_m \ln PS_m^{w,r})}{\sum_{r\in R^w} \exp(-\mu_m C_m^{w,r} + \beta_m \ln PS_m^{w,r})}, \ \forall\, w \in W, \forall\, m \in M, \forall\, r \in R^w, \tag{11}$$

where path-size penalty is defined as:

$$PS_m^{w,r} = \sum_{a\in r} \left(\frac{l_a}{l_r}\right)\left(\frac{1}{\sum_{r\in R^w} \delta_{m,a}^{w,r}}\right), \tag{12}$$

and route-based travel cost (generalized travel cost) for two classes are given as:

$$C_0^{w,r} = \sum_{a\in A} \delta_{0,a}^{w,r} F_0^{w,r} (\theta_0 l_a + \eta_0 t_a(q_a)), \tag{13}$$

$$C_1^{w,r} = \sum_{a\in A_0} \delta_{1,a}^{w,r} F_1^{w,r} (\theta_0 l_a + \eta_0 t_a(q_a)) + \sum_{a\in A_1} \delta_{1,a}^{w,r} F_1^{w,r} (\theta_1 l_a + \eta_1 t_a(q_a)). \tag{14}$$

Eq. (14) guarantees that for AV class, parts of the routes within the AD subnetwork have different generalized travel cost via different VoT (η_m) and VoD (θ_m) values, and different link travel times depending on PCU equivalent of class-specific flows (q_a) which is calculated based on Eqs. (2) and (3).

3.4.2. Impacts: network performance criteria

The most common performance criteria used in the literature for assessing the impacts of road network configurations are total travel cost (TTC), total travel time (TTT), and total travel distance (TTD) (Yang and Bell, 1998). Eqs. (15)–(17) represent these metrics, respectively. These values are based on equilibrium flows and travel times. Impacts of CVs and AVs in AD subnetwork in equilibrium conditions are based on the following formulae.

$$TTC = \sum_{a\in A_0} (\eta_0 \bar{t}_a + \theta_0 l_a)(\bar{f}_{0,a} + \bar{f}_{1,a}) + \sum_{a\in A_1} [(\eta_0 \bar{t}_a + \theta_0 l_a)\bar{f}_{0,a} + (\eta_1 \bar{t}_a + \theta_1 l_a)\bar{f}_{1,a}], \tag{15}$$

$$TTT = \sum_{a\in A} \bar{t}_a (\bar{f}_{0,a} + \bar{f}_{1,a}), \tag{16}$$

$$TTD = \sum_{a\in A} l_a (\bar{f}_{0,a} + \bar{f}_{1,a}). \tag{17}$$

3.5. Route-set generation

One particular importance of route-set generation for modeling AV behavior is to capture specific route sets that might become attractive for AVs due to the changes in their VoT, VoD, and PCU value. Considered route sets in traffic models must include these routes as well. For instance, in the case of Delft, any route that is (partially) within the AD subnetwork (potentially) has a lower travel cost for AVs. These changes might make some routes that at first sight seem long and unusual become relevant alternatives for AVs due to their lower costs. This indicates the need for new route-set generation approaches to generate realistic route sets for AVs.

Common route-set generation methods do not generate such routes but some methods have the potential to serve this purpose. In this study, the Monte Carlo labeling combination method introduced in (Catalano and Van Der Zijpp, 2001) is used with some adjustments to generate appropriate route sets for AVs. In addition to common labels (travel cost, travel time, travel distance), a label with a multiplier (with a value between 0 and 1) is used for the cost of links within the AD subnetwork to generate more routes that cross the AD subnetwork but

Table 2
Indexed travel impacts for different variants of AD subnetwork compared to the based case and AD everywhere scenario (checkmarks (✓) indicate road types on which AD is facilitated in each scenario and indexing is based on the base case scenario).

Network Type		No AD (base case)	AD subnetwork variants			AD everywhere
Freeways		–	✓	✓	✓	✓
Regional roads		–	–	✓	✓	✓
Main urban roads		–	–	–	✓	✓
Local roads		–	–	–	–	✓
Network Variant		**Main**	**Variant 1**	**Variant 2**	**Variant 3 (main)**	**Main**
AV Penetration Rate		**0%**	**50%**	**50%**	**50%**	**100%**
Parameter Ratio (X_{AV}/X_{CV})		–	$PCU_{AV}/PCU_{CV} = 0.90$ $VOT_{AV}/VOT_{CV} = 0.95$ $VOD_{AV}/VOT_{CV} = 0.85$			
Total Travel Cost	CV	100.00	49.92	49.89	49.88	0.00
	AV	0.00	47.79	46.89	46.50	88.98
	Overall	100.00	97.71	96.78	96.38	88.98
Total Travel Time	CV	100.00	49.83	49.74	49.72	0.00
	AV	0.00	50.03	49.97	49.95	98.50
	Overall	100.00	99.86	99.71	99.67	98.50
Total Travel Distance	CV	100.00	50.00	50.00	50.00	0.00
	AV	0.00	50.30	50.38	50.13	100.23
	Overall	100.00	100.30	100.38	100.13	100.23

are too expensive for CVs. This is to ensure that the longer routes within AD subnetwork which can become feasible due to higher efficiency of AD are included in the considered route sets for AVs. For generating routes for CVs, no adjustment has been made on the original method.

3.6. Solution algorithm

There are several solution algorithms in the literature for the MUC SUE problem. A review of these algorithms is provided in (Noriega and Florian, 2007). The problem with presented formulation in this paper can readily be solved using the solution method developed in (Wu et al., 2006) where the authors introduce an MUC extension of MSA algorithm.

4. Case study

A case study is used to demonstrate the impacts of AVs in AD subnetwork modeled with the proposed method. In this case, a network similar to the road network in Delft, The Netherlands is used in order to observe some practical issues related to road types in real networks. The network and demand patterns are based on a tutorial project for the transport modelling software package *OmniTRANS*. It includes 1151 links, 494 nodes and 22 zones.

Demand for AVs is considered via seven scenarios based on different market penetration rates of AVs. Three different network configurations and three network variants for the second configuration are used for experiments:

- Base case network: this is the reference point for comparison with all other cases and is the regular Delft network including all the links in Fig. 1 as none-AD links ($A_0 = A, A_1 = \varnothing$).
- AD subnetwork: this network is shown in Fig. 1 ($A_0 \cup A_1 = A, A_0 \cap A_1 = \varnothing$). The subnetwork for AD (main variant) covers 38% of the overall distance in the network. Moreover, two additional variants of this subnetwork (shown in Fig. 1) are used in scenario analysis to showcase the impacts of link selection for AD subnetwork.
- AD everywhere network: this is used to demonstrate the extreme impacts for comparisons and it includes all links in Fig. 1 as AD links ($A_1 = A, A_0 = \varnothing$).

There are several road types in this network representation. Apart from the connectors which are artificial links connecting zone centroids to the network, four major categories are recognized that signify network hierarchy, namely, freeways, regional roads, main urban roads, and local roads. Mentioned list is in the descending order in terms of network hierarchy. For the (main variant of) AD subnetwork, all local roads (lowest level according to network hierarchy) are considered infeasible for AD subnetwork and all freeways (highest level) are considered feasible. For the remaining road types, a selection is made based on road function, potential quality, traffic segregation, and complexity of relevant intersections.

Studied impacts are total travel cost, total travel time, and total travel distance which were introduced earlier. Furthermore, the distribution of impacts for each network type, network variant, demand scenario, road type, and user class is investigated.

Input parameters related to modeling AVs are provided in Table 1. There is no consensus in the literature on exact magnitude of changes in PCU, VoT, and VoD values as a result of AD and there is no possibility of validating different results at the moment. Therefore, we have chosen similar values to those used in (Puylaert et al., 2017) and performed a sensitivity analysis to demonstrate the sensitivity of outcomes to the input parameters. The parameters for the PSL model are also reported in Table 1. The base case demand and network data are from the base case in the Delft project in *OmniTRANS* software introduced earlier.

This case study using the AD subnetwork design method is implemented in MATLAB and the code is available from the authors upon request.

Ten scenarios using 7 demand patterns, 3 network configurations, and 3 network variants for the second configuration are considered in this study, and for each case, key performance indicators are calculated separately for each road type and each user class using the model. Furthermore, sensitivity analyses are performed for AD parameters used in the model. We focus the discussion on key performance indicators (TTC, TTT, TTD) with a distinction per road type, plus a sensitivity analysis. All numbers reported are indexed with respect to the base case scenario, unless stated otherwise in the caption.

Table 2 provides a comparison of key network performance indicators for three variants of AD subnetwork using 50% AV penetrate rate scenario including separate results for different classes. No AD with 0% AV penetration rate and AD everywhere with 100% AV penetration

Table 3
Indexed travel impacts for all network types, demand scenarios, and the main AD subnetwork variant (indexing is based on the base case scenario).

Network Type		No AD (Base Case)	AD Subnetwork (main variant)						AD Everywhere
AV Penetration Rate		**0%**	**10%**	**30%**	**50%**	**70%**	**90%**	**100%**	**100%**
Parameter Ratio (X_{AV}/X_{CV})		**PCU_{AV}/PCU_{CV} = 0.95** **VOT_{AV}/VOT_{CV} = 0.95** **VOD_{AV}/VOT_{CV} = 0.95**			**PCU_{AV}/PCU_{CV} = 0.90** **VOT_{AV}/VOT_{CV} = 0.95** **VOD_{AV}/VOT_{CV} = 0.85**				
Total Travel Cost	CV	100.00	89.97	69.94	49.88	29.90	9.96	0.00	0.00
	AV	0.00	9.71	29.11	46.50	65.05	83.58	92.84	88.98
	Overall	100.00	99.68	99.05	96.38	94.95	93.54	92.84	88.98
Total Travel Time	CV	100.00	89.94	69.86	49.72	29.79	9.92	0.00	0.00
	AV	0.00	10.04	30.08	49.95	69.82	89.65	99.55	98.50
	Overall	100.00	99.98	99.94	99.67	99.61	99.55	99.55	98.50
Total Travel Distance	CV	100.00	90.00	70.00	50.00	30.00	10.00	0.00	0.00
	AV	0.00	10.02	30.05	50.13	70.18	90.24	100.26	100.23
	Overall	100.00	100.02	100.05	100.13	100.19	100.24	100.26	100.23

scenarios represent the two ends of the spectrum with no impacts and highest impacts, respectively, as potential lower and upper bounds. Road types on which AD is facilitated in each scenario are indicated with checkmarks (✓) in relevant columns. Different variants of AD subnetwork as well as AD everywhere scenario are considered in order to provide insight into the impacts of higher distance coverage of AD subnetwork. As demonstrated in Table 2, TTC and TTT further improve in AD subnetwork variants that include more road types (more links). Moreover, TTD is slightly higher in variants 1 and 2 compared to the main variant. This can be explained by lower accessibility of AD subnetwork in these variants due to their lower network density that leads to rerouting to longer routes.

Table 3 summarizes the changes in total travel time, cost and distance for all demand scenarios, network configurations, and main network variants compared to the base case. A significant and steady decrease in total travel cost, a minor decrease in total travel time, and a minor increase in total travel distance are observed with increase in AV market penetration rate. The only exception is the decrease in total travel distance in AD everywhere scenario compared to AD subnetwork with 100% AV penetration rate. This is explained by the fact that most of the induced travel distance in AD subnetwork cases is the result of rerouting towards the subnetwork, whereas in the AD everywhere scenario there is no need for rerouting since AD is possible everywhere. Yet, there is an increase in travel distance in this case compared to the base case due to lower cost of distance and time for AVs.

There is a shift of traffic, as evidenced by total travel distance in Table 4, from local roads and freeways to regional roads and main urban roads. The pattern is evident in all scenarios with AVs and is intensified with higher AV penetration rates. On the other hand, travel time and cost in various road types follow a different trajectory. In local roads, travel time and cost are slightly lower compared to the base case but this is only due to less traveled distance. In freeways, the improvements in travel time and cost are more significant as a result of the higher efficiency gained through AD. Finally in regional roads and main urban roads, an improvement in travel cost is observed as a result of AD efficiency despite the increasing travel distance and time.

Since different values for the changes in AD parameters (i.e., PCU, VoT, and VoD) as a result of AD efficiency are reported in the literature and there is no real data for validation, it is appropriate to perform a sensitivity analysis in order to assess possible changes in results with deviations in these parameters. A summary of the sensitivity analyses for PCU, VoT, and VoD is demonstrated in Table 5. Rows with even numbers are eliminated; nonetheless, the presented results are sufficient to observe that changes in parameters within a realistic range of values have limited influence on the results. Obviously, the travel costs are the most sensitive measures as they are directly affected by the

Table 4
Indexed distribution of impacts for all user classes in different road types (indexing is based on the values of 'all roads' column in the base case scenario and numbers for connectors are eliminated).

Road Type		Freeways	Regional Roads	Main Urban Roads	Local Roads	All Roads
0% Penetration Rate (Base Case)						
Total Travel Cost		41.12	12.01	9.25	12.45	100.00
Total Travel Time		30.53	10.70	10.08	16.72	100.00
Total Travel Distance		49.86	13.09	8.56	8.92	100.00
50% Penetration Rate in AD Subnetwork (main variant)						
Total Travel Cost	CV	20.47	5.98	4.61	6.23	49.88
	AV	18.00	5.52	4.37	5.93	46.50
	Overall	38.47	11.50	8.98	12.16	96.38
Total Travel Time	CV	15.07	5.29	5.02	8.37	49.72
	AV	15.00	5.47	5.28	8.00	49.95
	Overall	30.07	10.76	10.30	16.37	99.67
Total Travel Distance	CV	24.93	6.54	4.28	4.46	50.00
	AV	24.82	6.81	4.51	4.23	50.13
	Overall	49.75	13.35	8.79	8.68	100.13
90% Penetration Rate in AD Subnetwork (main variant)						
Total Travel Cost	CV	4.08	1.19	0.92	1.25	9.96
	AV	32.30	9.91	7.85	10.70	83.58
	Overall	36.38	11.10	8.78	11.95	93.54
Total Travel Time	CV	2.99	1.05	1.00	1.68	9.92
	AV	26.76	9.78	9.49	14.45	89.65
	Overall	29.75	10.83	10.49	16.13	99.55
Total Travel Distance	CV	4.99	1.31	0.86	0.89	10.00
	AV	44.67	12.26	8.11	7.61	90.24
	Overall	49.66	13.57	8.97	8.50	100.24

values for VoD and VoT. However, when looking at TTT and TTD, the impacts are minimal. It is essential to notice that these results are valid for a certain range of parameters that we considered sensible; however, larger deviations might cause deeper and more significant effects, not only on route choice but also on other travel choices which might require more elaborate modeling as well.

5. Discussion and conclusions

In this study, different scenarios are used to gain insight into the impacts of a possible AD network configuration (AD subnetwork). A regular network with no AV market penetration is considered as the base case in order to provide a point of reference for the relative

Table 5
Sensitivity analysis summary for 90% AV market penetration rate scenario in the main variant of AD subnetwork (indexing is based on values of the base case).

Analyzed AV Parameter	Parameter Ratio (X_{AV}/ X_{CV})	Vehicle Type	Total Travel Cost	Total Travel Time	Total Travel Distance	Other AV Parameters
Passenger Car Unit (PCU)	**0.7**	CV	9.88	9.81	9.94	$\mathbf{VOT_{AV}/VOT_{CV} = 0.95}$ $\mathbf{VOD_{AV}/VOT_{CV} = 0.85}$
		AV	83.03	88.60	89.99	
		Overall	92.92	98.42	99.93	
	0.9	CV	9.93	9.94	9.94	
		AV	83.46	89.61	89.98	
		Overall	93.40	99.55	99.92	
	1.1	CV	10.02	10.12	9.94	
		AV	84.24	91.44	89.96	
		Overall	94.26	101.56	99.90	
Value of Time (VoT)	**0.7**	CV	9.93	9.94	9.94	$\mathbf{PCU_{AV}/PCU_{CV} = 0.90}$ $\mathbf{VOD_{AV}/VOT_{CV} = 0.85}$
		AV	78.34	89.65	90.14	
		Overall	88.28	99.57	100.08	
	0.9	CV	9.93	9.94	9.94	
		AV	82.44	89.63	90.01	
		Overall	92.38	99.55	99.95	
	1.1	CV	9.93	9.92	9.94	
		AV	86.52	89.59	89.89	
		Overall	96.45	99.53	99.82	
Fuel efficiency (VoD)	**0.7**	CV	9.93	9.94	9.94	$\mathbf{PCU_{AV}/PCU_{CV} = 0.90}$ $\mathbf{VOT_{AV}/VOT_{CV} = 0.95}$
		AV	78.21	89.63	90.13	
		Overall	88.15	99.57	100.06	
	0.9	CV	9.93	9.94	9.94	
		AV	85.21	89.61	89.93	
		Overall	95.14	99.53	99.87	
	1.1	CV	9.93	9.92	9.94	
		AV	92.17	89.57	89.75	
		Overall	102.10	99.51	99.69	

changes in each scenario. Also, a scenario where AD is allowed everywhere and all the vehicles in the network are AVs (i.e. 100% AV penetration) is simulated to illustrate the highest possible impacts.

Based on this study, the differences in impacts between AD everywhere and AD subnetwork with 100% penetration rate are not large. This means that AD subnetwork with high AV penetration rates can deliver a great share of benefits obtainable from AD everywhere (i.e., AD subnetwork with 100% penetration rate can deliver 64% of cost benefits of AD everywhere with 100% penetration rate). Given that AD everywhere is only possible for level 5 AVs and that AD subnetwork introduced here is suitable for levels 3–4 AVs as well, it can be concluded that it is possible to realize most benefits of level 5 automation in urban regions with AD subnetwork only having levels 3–4 AVs. It should be noted that only route choice is considered here and that changes in destination and mode choice due to usage of AVs can also affect network performance. As AVs become more appealing in time, they can attract users of other modes. Moreover, facilitating AD in certain parts of the network can affect location and destination choices in long term in favor of zones with better accessibility to AD-friendly parts of the network, especially given the relatively large impact on TTC (which is an input for choices of mode and destination).

The results support the expectation that AV market penetration rate is the dominating factor to affect the impacts. There is a sharp change in the impacts after 40% AV penetration rate (partially due to the changes in parameters) and the effects become more significant with higher AV penetration rates. Although, the overall impacts, even in the AD everywhere scenario, are rather low with maximum observed changes in TTC, TTT and TTD being 11.02%, 1.5% and 0.26%, respectively.

Sensitivity analysis shows that the parameters individually have limited impact at network level in urban regions, and their deviations, within a realistic range, do not affect the results significantly. It appears that only the combination of all three AD parameters (i.e. PCU, VoT, and VoD) along with the new considered route sets for AVs can lead to significant changes.

The observed patterns in the shift of traffic between different road types are expected to repeat themselves with AD subnetwork deployment in different network types since there is a clear rationale for this shift; AD subnetwork is more efficient and desirable for AVs and is expected to attract more traffic. However, main urban roads and regional roads within the AD subnetwork are used more than freeways due to their higher accessibility (i.e., for most origins and destinations, the closest access point to the AD subnetwork is via main urban roads and regional roads).

As for the AD subnetwork distance coverage, the variants including more road types (higher coverage) are shown to be more effective in terms of network performance, yet the increase in the performance is not necessarily linear. On the other hand, including more links in the AD subnetwork requires a higher adjustment cost. Therefore, finding the optimal trade-off between adjustment costs and benefits acquired from the AD subnetwork calls for optimization methods. Changes in general demand level (congestion level) can affect the optimal link choice as well.

Regarding the method proposed in this study, we believe the mechanisms are valid and generalizable for assessing the route choice impacts of AD at network level. Although, there are limitations to this approach and improvements to the model are possible through the following model components that constitute the research agenda for this topic:

- *Quantitative optimization methods:* the choice of links in this study is based on a qualitative analysis. Another alternative is to define feasible links with the same procedure and formulate a bi-level optimization problem to find the optimal link choice (i.e., upper level decisions) within feasible links in the AD subnetwork in equilibrium conditions (i.e., lower level optimization). In addition to travel cost, time, and distance, other criteria could be specified to analyze trade-offs between adjustment costs and benefits in the optimization problem.
- *Dynamic traffic assignment (DTA):* AVs are expected to cause changes in fundamental diagrams and flow-density relationships. These

changes as well as queueing and spill back can accurately be captured in DTAs. Moreover, intersections are key elements in urban networks and can affect travel time; properly modeling the behavioral differences of CVs and AVs around intersections demands multi-class DTAs with elaborate node models. However, using these models for NDP is extremely challenging due to their computation time and data requirements.

- *Elastic demand:* AV demand and its adaptations over time as a response to the quality of service in the network can be modeled using elastic demand as opposed to scenario based demand. This can include several travel choices such as AV ownership, location, destination, mode, and time of the day choice.
- *Time dimension considerations:* deployment of AD subnetwork (or any other network configuration) is a gradual and long-term process. It also depends on AD development path in the future which is uncertain. This development over time subject to different uncertainties needs to be taken into account for infrastructure investment decisions. An appropriate AD network design method should include the time dimension and proper stochastic models to deal with mentioned uncertainty.

6. Recommendations

Based on this study, we recommend municipalities and metropolitan regions to start considering the notion of facilitating AD and making urban regions AD-friendly to guarantee safety for all road users and to aid in having a smooth transition period to full automation. This requires answering the question of “on which roads do we facilitate AD?” In order to answer this question, trade-offs between adjustment costs and gains in network performance have to be taken into account. As mentioned in the research agenda, more comprehensive transport models are necessary to consider these trade-offs and to thoroughly investigate AD impacts on urban regions.

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